Grenze International Journal of Engineering and Technology, June Issue

Crack Identification in Bridge Infrastructure using a Convolutional Neural Network

Kuldeep Vayadande[1], Sahil Jagtap[2], Bhushan Sadmake[3], Nishka Mane[4], Ketan Singh[5] and Bhavika Chavan[6]
[1-6]Department of Information Technology, Vishwakarma Institute of Technology, Pune, India'
Email: kuldeep.vayadande@gmail.com,{sahil.jagtap21, bhushan.sadmake21, nishka.mane211, ketan.singh21, bhavika.chavan21}@vit.edu

***Abstract*— As the backbone of transportation networks, the structural integrity of bridges is paramount for ensuring public safety and the efficient flow of goods and people. The traditional method that is Manual inspection methods for crack detection are labor intensive and often subjected to human error. This research explores an innovative approach to address this challenge by leveraging Convolutional Neural Networks for automated crack identification in bridge infrastructure. The proposed model employs a dataset encompassing concrete bridge conditions, and crack manifestations to train and evaluate the selected model. The accuracy of the prediction was verified by the test sets. The introduced model demonstrated a crack detection accuracy of 99% without relying on pre-training. Experimental results indicated that, when compared to existing classification models, the suggested model exhibited superior performance. Notably, the proposed model surpassed the ResNet50 model in terms of effectiveness.**

***Index Terms*— Deep learning, Image Processing, Classification, Crack detection, Concrete bridge deck.**

I. Introduction

The maintenance and safety of critical infrastructure, such as bridges, play a vital role in ensuring the well-being of society. One of the necessary challenges in the given domain is the early detection and identification of structural cracks. The traditional methods of crack detection that is manual inspection often fall short in terms of efficiency and precision. The manual inspections are both labour-intensive and time consuming. The objective of this project is to utilize the capabilities of deep learning to create an automated and accurate Crack Identification system. Increasing advancements in computer vision and deep learning technologies offer promising solutions to address this challenge effectively. The given project focuses on the development and implementation of a CNN for Crack Identification in Bridge Infrastructures. Leveraging state of the art techniques into image recognition, the CNN is trained to autonomously to analyze visual data and discern the presence of cracks in bridge components. This research is dedicated to the implementation and comparison of three distinct CNN models —the proposed CNN model, VGG16 model, and ResNet50 for Crack Identification in Bridge Infrastructure. Each model brings its unique architecture and features to the forefront, allowing for a comprehensive evaluation of their efficacy in addressing the challenges associated with crack detection. By employing three different CNN architectures, we aim to assess their individual strengths and weaknesses in the context of bridge infrastructure.

Grenze ID: 01.GIJET.10.2.261_1

II. Literature Survey

The automatic inspection approach introduced in [1] for bridges demonstrated an impressive overall accuracy of 92.11% in detecting cracks within bridge images, successfully navigating through noisy and intricate visual contexts. The utilization of a sliding window-based technique, coupled with wavelet and Gabor filter features, proved to be particularly effective in crack detection for bridge images. Interestingly, when examining feature vectors from "complex" and "normal" photos independently, the system showed improved accuracy. The study in [2] represented the necessity for a more preprocessing technique capable of accommodating various types of bridge images. The paper suggests an automated method for detecting bridge cracks employing lightweight vision models, which is particularly integrating the YOLO v4 algorithm with the lightweight networks like GhostNet ,DenseNet and MobileNet. YOLO v4, an enhanced iteration of YOLO v3, includes network architecture, activation functions, training methods, and data processing optimizations. The proposed approach demonstrates notable advantages in precision, speed, and model size when juxtaposed with current methods for bridge crack detection. The study in [3] proposes a complete model for crack detection that uses a convolutional neural network and is specifically designed for concrete bridge crack detection. This model extracts utilizing an Atrous Spatial Pyramid Pooling module to provide multiple scale contextual data, reduces computational cost via depth wise separable convolution, and atrous convolution to provide an extended receptive field without sacrificing resolution. Interestingly, without pre-training, the suggested model outperformed classic classification models like Resnet18, Resnet34, Resnet50, Vgg16, and Vgg19, with a detection accuracy of 96.37%. The paper [4] introduces a novel approach for detecting cracks and measuring parameters in bridges through the application of convolutional neural networks (CNNs). This method seamlessly incorporates digital images processing into CNN, enhancing the precision of images classification and facilitating crack length measurement. The crack images are meticulously labeled as positive or negative samples, and subsequently segregated into training and validation sets. The effectiveness of the parameter detection algorithm is validated using the crack length parameter as an illustrative example. The paper [5] introduces a vision-centric method for detecting cracks in concrete bridge decks, employing a 1D-CNN-LSTM algorithm. This algorithm operates in the frequency domain, where images undergo a transformation into the frequency domain as part of the preprocessing stage. The utilization of one-dimensional convolutional neural networks (1D-CNNs) is highlighted for feature extraction and learning from flattened image frequency signals. It is very important to consider that the study complies within the ethical guidelines and does not use any human or animal subjects. In infrastructure maintenance given in [6], the traditional error-prone inspection methods are evolving with the integration of computer vision, particularly Convolutional Neural Networks (CNNs). This advanced CNN framework, featuring ten convolutional layers and a GAN, allows precise pixel-by-pixel crack segmentation. Including networks that are closely monitored and fully convolutional networks (FCN) refines the process, utilizing multi-level feature aggregation, guided filtering, and Conditional Random Fields (CRFs). The model demonstrates outstanding results in F-score, recall, and precision values, surpassing conventional methods. This study highlights the transformative potential of CNNs in modernizing infrastructure maintenance, providing an efficient solution for crack detection. The research in [7] ensures long-term durability and structural integrity of concrete structures which requires the identification and categorization of Alkali-Silica Reaction (ASR) cracks. Traditional visual inspection methods often lack accuracy and efficiency. A two-phase computer vision algorithm for ASR fracture detection and classification is presented in this research. Pre-trained CNN models are assessed in the first phase, and InceptionV3 is shown to be the best performer. A Features Enhancement Process is introduced in the second phase to improve the visibility of ASR cracks against complex backdrops. The technique obtains a validation accuracy of 94.07% when combined with texture analysis algorithms. The article [8] focuses on the use of a two-level deep learning interface for the detection and evaluation of the cracks, with a particular focus on developing countries. According to the Traditional method, the visual inspection of the bridges has been the best method for monitoring , but it has proved to be time consuming, costly and prone to errors. To solve these problems, the give study represents the use of the YOLOv5 model for detection. Additionally, the study uses the U-Net model, which can measure cracks height and width and also the area per pixel for crack segmentation. The article [9] introduces an automatic detection system designed to detect sequentially. This approach involves adaptive learning leveraging pre-trained convolutional neural network (CNN) models such as MobileNetV2, ResNet101, VGG16, and InceptionV2. After all testing, MobileNetV2 emerged as the winner. The current explosive detection method is not equipped to handle this situation. The given work represents the potential and importance for deep learning and processing of the images to be accurate and efficient that is able to provide significant promise for good monitoring of buildings, bridges, and other structures. The paper [10] underscores the importance of early crack detection in ensuring structural safety and underscores the drawbacks of conventional visual inspections and vehicle-based methods for bridges, which are not only inefficient but also pose safety risks. In a bid to improve the efficiency and cost-effectiveness of structural health monitoring, the paper introduces an innovative approach that integrates deep learning with attention mechanisms and employs the UNet network to detect cracks. This research provides a sturdy solution to enhance the recognition of cracks in structural assessments more effectively. In [11], the concrete structure safety assessment, it is very important to detect and evaluate damage, which is very challenging with traditional methods for the indicators like precast concrete dimension deviations, abnormal vibration responses, and reduced structural bearing capacities. The given study represents the application of Deep learning for addressing important issues related to damage inspection in concrete structures of the bridge, understanding its potential to revolutionize the engineering practices by improving the automation and efficiency of damage assessment. The study [12] shows the use of adaptive learning which is a widely used method in design. Deep learning is for explosive detection. Transformational learning involves using the pre trained big data models to improve the learning process for a specific task or data. The Researchers aim to improve crack detection algorithms in rocks using transfer learning. This approach is important to reduce runtime and data requirements for certain applications such as explosion detection. The work in [13] solves the network task of pavement crack detection using images and local transformers. Transformer networks are very powerful in processing data arrays and are promising in graphical processing as well. The research will involve the development of a combination of electronic devices to better detect pavement cracks in CCD captured images. This study is important because it explores new ways to detect cracks which is important for monitoring safety. The paper [14] represents the method that has better performance and is compared to the book method for detecting cracks in complex areas such as mud. This method uses deep learning using large datasets of rock fragments and small datasets of soil and also the rock fragments. First of all, a pretrained model was created based on scattered data and then an improved model was created using soil and rock data. The given model can use drones to survey steep terrain and provide rapid assessment and early warning of geological disasters. The paper [15] represents the importance of bridge maintenance and the problems caused by cracks in concrete structures. It presents a new approach that uses deep learning models for detecting and segmenting connections between cracks. The authors of this article have compiled the specific information for closing cracks and modified the You Only Look at One algorithm, turning CR YOLO into more accurate crack detection. They also reduced visual artifacts by improving the PSPNet algorithm to separate cracked bridges from the non-cracked areas.

III. METHODOLOGY

The methodology for the development of our Crack Identification in Bridge Infrastructure system encompasses several phases. Below figure 1 shows the various phases

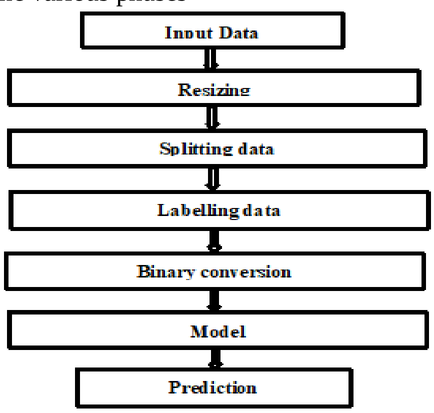


Fig. 1: Proposed model diagram

Input Data: The input here is a dataset containing images. Pictures of several bridges both with and without cracks are there in the dataset . In order to classify images, they are separated into two groups positive that are containing cracks and negative that are not having crack, and these two are kept in different folders. There are 20,000 photos of each group, total of 40,000 photos with RGB channels and 227 × 227-pixel sizes are present.
Resizing: We have images of 227x227 pixels in our dataset. we converted all the images to a constant pixel ratio that is 120x120.

Splitting: In order to make a good model for evaluation, the data is divided into training and testing. The training results contain 70% of the data out of that the 20% of the training data will be used for validation, the remaining 80% will be used for actual training the and procedure. the rest of remaining 30% will be used for testing purpose. Neural network (CNN) Structure is important.

Labelling: The labeling process will associate each image in the dataset with a class label that indicates whether the image contains cracks or not. Positive samples are labeled POSITIVE and negative samples are labeled NEGATIVE The data generation process combines positive and negative patterns to provide a labeled data set that forms the basis for modelling.

Binary Conversion: In the binary conversion process, each image in the dataset was assigned a binary label POSITIVE if it contained a crack and "NEGATIVE if it did not. The labeled dataset, thus formed, served as the basis for training the Convolutional Neural Network (CNN) to classify images as either containing cracks or being crack-free.

Model: In this research, the dataset is trained using three distinct convolutional neural networks (CNN) architectures: the proposed model, VGG16, and ResNet50. both VGG16 and ResNet50 are pre-trained models. In the given architecture of the proposed model, a maximum pooling layer is placed after three convolutional layers to reduce the spatial dimension. Convolutional layers use padding and use the relu activation function to retain spatial information. The Global Median layer compresses spatial data for providing a more accurate representation. The fully connected system features a thick layer of 512 units and relu activation following the release process to prevent overfitting. The final layer is dense and perfect for binary functions since it has a unit and sigmoid function. The workflow of the project is shown in figure 2. The model performance comparison of all the models is shown in the table 1. Figure 5 shows the Computational Efficiency Comparison of CNN models.

Prediction: The model will predict whether the crack is there or not in the new test image including human-readable labels ('Negative' or 'Positive') and confidence scores.

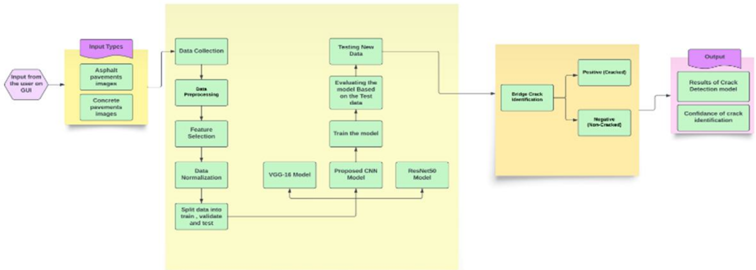


Fig. 2: Workflow Diagram

TABLE I: MODEL PERFORMANCE COMPARISON W.R.T ACCURACY

Model	Accuracy
Proposed CNN Model	99%
VGG16	99.28%
ResNet50	95.06%

Algorithm 1: Proposed CNN model

1. **Initialization:**
- At the first step, we Define the CNN architecture for specifying the number and types of layers like convolutional, pooling and fully connected.
- Initialize weights and biases.

2. **Forward Pass:**
- In forward pass, we Feed an image into the network.
- Once the images are feeded we Conduct convolutional and pooling operations to extract features.
- Flatten the resulting output and transmit it through fully connected layers.

III.

- Implement activation functions for example the ReLU following each layer.

3. **Loss Calculations:**

- Determine the difference between the predicted output and the actual target by applying a loss function, for instance and cross entropy.

4. **Backward Pass (Backpropagation):**

- Calculate the gradients of the loss concerning the parameters like weights and biases through the process of backpropagation.
- Adjust the parameters by employing an optimization algorithm such as adams optimiser, stochastic gradient descent etc.

5. **Training Loop:**

- Iterate through steps 2 to 4 either for the predefined number of epochs.

RESULTS AND DISCUSSION

A. Model Evaluation: In this research, the outcomes of proposed model are truly commendable, underscoring the efficacy of the CNN model in crucial task of crack identifications within bridge infrastructure. The remarkably low-test loss of 0.03024 reflects the model's precision in making accurate predictions on the test set. With an impressive test accuracy of 99%, the model showcases a high success rate in classifying positive and negative samples, indicative of its robust performance. The substantial R-squared score of 0.95998 adds a layer of depth, affirming the model's capacity to elucidate a significant portion of the variability in the target variable. Detailed analysis of the distribution in Figure 3 vividly demonstrates the power of the model, which not only shows high precision, recall and F1 score values for negative and positive classes, but also has an overall accuracy of up to 99%.Collectively, these results underscore the potency and reliability of proposed CNN model, positioning it as a formidable tool for the critical task of crack detection in bridge infrastructure, with implications for enhancing structural safety and maintenance practices. Accuracy and loss curve of proposed model is shown in Figure 4 and Figure 6 shows the Precision-Recall comparison of proposed CNN model. Figure 7 shows GUI results of crack identification with human-readable labels and confidence scores.

Classification Report :

	precision	recall	f1-score	support
NEGATIVE	0.99	0.99	0.99	917
POSITIVE	0.99	0.99	0.99	883
accuracy			0.99	1800
macro avg	0.99	0.99	0.99	1800
weighted avg	0.99	0.99	0.99	1800

Fig 3: Classification reports

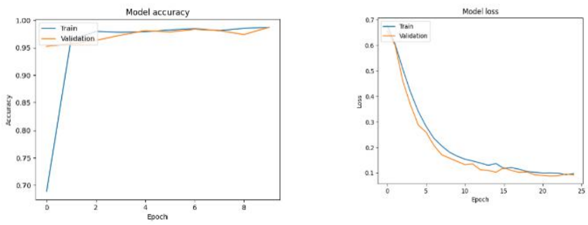


Fig 4: accuracy and loss evolution graph

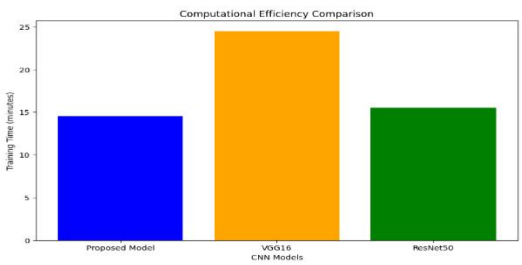


Fig 5: Computational Efficiency Comparison of CNN Models for Crack Identification

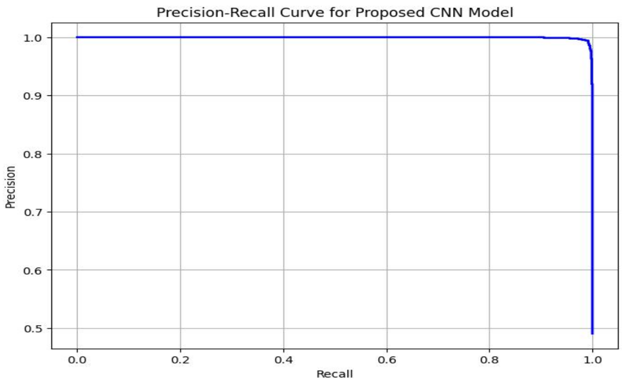


Fig 6: Precision-Recall comparison of proposed CNN model

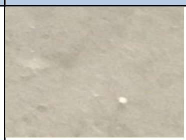
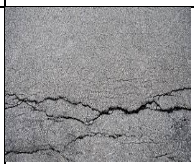
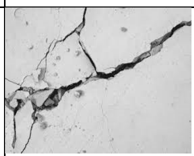
Sr no.	Input	Predicted Output
1.		Result: Negative (Not Crack) Confidence: [0.001283]
2.		Result: Positive (Crack) Confidence: [0.999953]
3.		Result: Negative (Not Crack) Confidence: [0.002281]
4.		Result: Positive (Crack) Confidence: [0.999999]
5.		Result: Positive (Crack) Confidence: [1.]

Fig 7: GUI results of crack identification with human-readable labels ('Negative' or 'Positive') and confidence scores.

B. Confusion Matrix : The level of detail provided by the confusion matrix shown in Figure 8 adds to the analysis which is used for providing an understanding of the positive, negative, negative and negative spects.

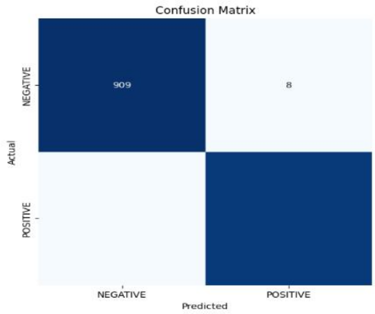


Fig 8: Classification reports

C. Comparison with existing model: several recent studies have developed predictive models for bridge crack detection using various machine learning approaches. The accuracy of the suggested CNN model is compared with a few other models in the table below (Table 2).

TABLE II. COMPARISON WITH EXISTING MODELS

Model	**Accuracy**
Wavelet analysis + SVM [1]	92.11%
CNN + ASPP module [3]	96.37%
CNN [4]	95%
Proposed CNN Model	**99%**

IV. CONCLUSION

In conclusion the project using neural networks (CNN) for the purpose of crack detection in bridge construction has shown good results and . The CNN model trained on data of images identifying cracked and non-cracked structures showed high accuracy in classifying objects. The suggested CNN method was trained, validated, and tested using more than thousands of photos of intact, fractured concrete bridges. On training, validation, and testing data, the CNN model obtained accuracy rates of 99%, 98,98.6%, and 99%, respectively. By using this framework, the training models can be successfully deployed to detect fractures with high accuracy in big unlabeled photos. More information can still be added to the model to increase performance even while negative and negative impacts are adequate for use. Although the proposed model was able to perform better than the ResNet50 model but the suggested model was not able to outperform VGG16's accuracy. The proposed approach was contrasted with current deep-learning techniques.

FUTURE SCOPE

The future scope of the project is very promising and diverse. Beyond the bridges, the proposed model can be extended to identify the structural issues in various types of infrastructure for contributing to a broader impact across the civil engineering domains. Collaborating with the industry stakeholders and integrating the model into real world inspection processes could facilitate the early detection and could enhance structural health monitoring. Further advancements might involve the integration of multimodal data for a more comprehensive analysis, and also the integration of IOT devices such as drones or sensors for the purpose of data collection for the exploration of predictive maintenance strategies, and the development of fully automated inspection systems. Continuous refinement of the proposed CNN model, global collaboration, and staying alongside of emerging technologies in artificial intelligence and civil engineering will be essential for the sustainable success and impact of the project.

REFERENCES

[1] Chanda, S. et al. (2014) Automatic Bridge Crack Detection: A Texture Analysis-Based Approach In: El Gayar, N., Schwenker, FF., andSuen, C. (eds) Artificial neural networks in pattern recognition ANNPR 2014. Lecture Notes in Computer Science, vol. 8774. Springer, Cham. https://doi.org/10.1007/978-3-319-11656-3_18

[2] Zhang, Jian; Qian, Songrong; and Tan, Can (2022). Automated bridge crack detection method based on lightweight vision models Complex &intelligent systems 9. 1–14. 10.1007/s40747-022-00876-6.

[3] Xu, H.; Su, X.; Wang, Y.; Cai, H.; Cui, K.; Chen, X. Automatic Bridge Crack Detection Using a Convolutional Neural Network Appl. Sci. 2019, 9, 2867. https://doi.org/10.3390/app9142867

[4] x. JIA and w. LUO, "Crack Damage Detection of Bridge Based on Convolutional Neural Networks," 2019 Chinese Control and Decision Conference (CCDC), Nanchang, China, 2019, pp. 3995–4000, doi: 10.1109/CCDC.2019.8833336.
[5] Zhang, Q., Barri, K., Babanajad, S. K., & Alavi, A. H. (2021). Real-Time Detection of Cracks on Concrete Bridge Decks Using Deep Learning in the Frequency Domain Engineering, 7(12), 1786–1796. https://doi.org/10.1016/j.eng.2020.07.026
[6] Hafz Suliman Munawar1 · Ahmed W. A. Hammad1 · S. Travis Waller2 · Md Rafqul Islam3, Modern Crack Detection for Bridge Infrastructure Maintenance Using Machine Learning, Human-Centric Intelligent Systems (2022)
[7] Andy Nguyen, Vahidreza Gharehbaghi b , Ngoc Thach Lec, Lucinda Sterling d, Umar Inayat Chaudhry e, Shane Crawford f, ASR crack identification in bridges using deep learning and texture analysis, Published by Elsevier Ltd.
[8] H. Inam, N. U. Islam, M. U. Akram, and F. Ullah, “Smart and Automated Infrastructure Management: A Deep Learning Approach for Crack Detection in Bridge Images,” Sustainability, Jan. 18, 2023. [Online]. Available: https://doi.org/10.3390/su15031866
[9] S. B. Ali, R. Wate, S. Kujur, A. Singh and S. Kumar, "Wall Crack Detection Using Transfer Learning-based CNN Models," 2020 IEEE 17th India Council International Conference (INDICON), New Delhi, India, 2020, pp. 1-7, doi: 10.1109/INDICON49873.2020.9342392.
[10] Yuan, H.; Jin, T.; Ye, X. Modification and Evaluation of Attention-Based Deep Neural Network for Structural Crack Detection. Sensors 2023, 23, 6295. https://doi.org/10.3390/s23146295
[11] Jiangpeng Shu, Zhenfen Jin, Deep Learning-Based Damage Inspection for Concrete Structures, Artificial Intelligence and Machine Learning Techniques for Civil Engineering, 10.4018/978-1-6684-5643-9.ch002, (19-45), (2023).
[12] N. Sharma, R. Dhir, and R. Rani, "Crack Detection in Concretes using Transfer Learning," in IEEE Access.
[13] XU, Z., GUAN, H., KANG, J., et al., “Pavement crack detection from CCD images with a locally enhanced transformer network”, International Journal of Applied Earth Observation and Geoinformation, v. 110, pp. 102825, 2022. doi: http://dx.doi.org/10.1016/j.jag.2022.102825.
[14] HE, K., ZHANG, X., REN, S., et al., “Deep residual learning for image recognition”, IEEE Proceedings on Computer Vision and Pattern Recognition (CVPR), v. 2021, pp. 770–778. 2016.
[15] J. Zhang, S. Qian, and C. Tan, “Automated bridge surface crack detection and segmentation using computer vision-based deep learning model,” Engineering Applications of Artificial Intelligence, vol. 115, p. 105225, Oct. 2022, doi: 10.1016/j.engappai.2022.105
[16] K. Vayadande, T. Adsare, T. Dharmik, N. Agrawal, A. Patil and S. Zod, "Cyclone Intensity Estimation on INSAT 3D IR Imagery Using Deep Learning," 2023 International Conference on Innovative Data Communication Technologies and Application (ICIDCA), Uttarakhand, India, 2023, pp. 592-599, doi: 10.1109/ICIDCA56705.2023.10099964.
[17] K. Vayadande, U. Shaikh, R. Ner, S. Patil, O. Nimase and T. Shinde, "Mood Detection and Emoji Classification using Tokenization and Convolutional Neural Network," 2023 7th International Conference on Intelligent Computing and Control Systems (ICICCS), Madurai, India, 2023, pp. 653-663, doi: 10.1109/ICICCS56967.2023.10142472.
[18] K. Vayadande, P. Narkhede, S. Nikam, N. Punde, S. Hukare and R. Thakur, "Facial Emotion Based Song Recommendation System,"2023 International Conference on Computational Intelligence and Sustainable Engineering Solutions (CISES), Greater Noida, India, 2023, pp. 240-248, doi: 10.1109/CISES58720.2023.10183606.
[19] Vayadande, K. et al. (2024). Traffic Sign Recognition System Using YOLO: Societal System for Safe Driving. In: Pawar, P.M., et al. Techno-Societal 2022. ICATSA 2022. Springer, Cham. https://doi.org/10.1007/978-3-031-34648-4_16
[20] K. Vayadande, T. Adsare, N. Agrawal, T. Dharmik, A. Patil and S. Zod, "LipReadNet: A Deep Learning Approach to Lip Reading," 2023 International Conference on Applied Intelligence and Sustainable Computing (ICAISC), Dharwad, India, 2023, pp. 1-6, doi: 10.1109/ICAISC58445.2023.10200426.
[21] K. Vayadande, V. Ingale, V. Verma, A. Yeole, S. Zawar and Z. Jamadar, "Ocular Disease Recognition using Deep Learning," 2022 International Conference on Signal and Information Processing (IConSIP), Pune, India, 2022, pp. 1-7, doi: 10.1109/ICoNSIP49665.2022.10007470.
[22] K. Vayadande et al., "Heart Disease Prediction using Machine Learning and Deep Learning Algorithms," 2022 International Conference on Computational Intelligence and Sustainable Engineering Solutions (CISES), Greater Noida, India, 2022, pp. 393-401, doi: 10.1109/CISES54857.2022.9844406.
[23] Classification of Depression on social media using Distant SupervisionKuldeep Vayadande, Aditya Bodhankar, Ajinkya Mahajan, Diksha Prasad, Shivani Mahajan, Aishwarya Pujari and Riya DhakalkarITM Web Conf., 50 (2022) 01005 DOI: https://doi.org/10.1051/itmconf/20225001005.
[24] K. Vayadande, S. Bhemde, V. Rajguru, P. Ugile, R. Lade and N. Raut, "AI-Based Image Generator Web Application using OpenAI’s DALL-E System," 2023 International Conference on Recent Advances in Science and Engineering Technology (ICRASET), B G NAGARA, India, 2023, pp. 1-5, doi: 10.1109/ICRASET59632.2023.10420306.
[25] K. Vayadande et al., "Heart Disease Prediction using Machine Learning and Deep Learning Algorithms," 2022 International Conference on Computational Intelligence and Sustainable Engineering Solutions (CISES), Greater Noida, India, 2022, pp. 393-401, doi: 10.1109/CISES54857.2022.9844406.
[26] P. Kunekar, K. Vayadande, O. Kulkarni, K. Ingale, R. Kadam and S. Inamdar, "OCR based Cheque Validation using Image Processing," 2023 5th Biennial International Conference on Nascent Technologies in Engineering (ICNTE), Navi Mumbai, India, 2023, pp. 1-5, doi: 10.1109/ICNTE56631.2023.10146687.

[27] K. Vayadande et al., "Heart Disease Prediction using Machine Learning and Deep Learning Algorithms," 2022 International Conference on Computational Intelligence and Sustainable Engineering Solutions (CISES), Greater Noida, India, 2022, pp. 393-401, doi: 10.1109/CISES54857.2022.9844406.
[28] Vayadande, K. et al. (2024). Traffic Sign Recognition System Using YOLO: Societal System for Safe Driving. In: Pawar, P.M., et al. Techno-Societal 2022. ICATSA 2022. Springer, Cham. https://doi.org/10.1007/978-3-031-34648-4_16
[29] Vayadande, K. et al. (2024). Heart Disease Prediction Using Machine Learning Techniques: A Survey for Societal Care and Information. In: Pawar, P.M., et al. Techno-societal 2022. ICATSA 2022. Springer, Cham. https://doi.org/10.1007/978-3-031-34644-6_37
[30] Rawate, S., Vayadande, K., Chaudhary, S., Manmode, S., Suryavanshi, R., Chanda, K. (2024). Fashion Classification Model. In: Pawar, P.M., et al. Techno-societal 2022. ICATSA 2022. Springer, Cham. https://doi.org/10.1007/978-3-031-34644-6_7