Indonesian Journal of Electrical Engineering and Computer Science
Vol. 34, No. 2, May 2024, pp. 1072~1080
ISSN: 2502-4752, DOI: 10.11591/ijeecs.v34.i2.pp1072-1080

Classifying flexible pavement defects using hybrid machine learning approach

Jaykumar Soni, Rajesh Gujar
Department of Civil Engineering, Pandit Deendayal Energy University, Gandhinagar, India

Article Info

Article history:

Received Dec 29, 2023
Revised Feb 21, 2024
Accepted Feb 22, 2024

Keywords:

Convolutional neural network
Machine learning
Pavement defects
Pavement management system
Support vector machine

ABSTRACT

The transportation infrastructure sector significantly impacts a country's gross domestic product (GDP), particularly in developing nations striving to manage and maintain road networks as valuable assets. While asset generation is integral, the more intricate challenge lies in effective maintenance. Pavement monitoring, a crucial component of pavement maintenance and management systems (PMMS), evaluates defect severity, road maintenance prioritization, and maintenance types. To enhance road health monitoring, the present study introduces a hybrid machine learning (ML) method, integrating support vector machine (SVM) and convolutional neural network (CNN). The proposed semi-automated detection system aims to reduce human supervision in traditional surveys, thereby cutting down the cost of pavement distress maintenance The research utilizes data collected by the authors from Ahmedabad city, Gujarat, following Indian road congress (IRC) guidelines for defect selection. Training involves 1,000 images for each crack type, with testing on 100 images. Results indicate that the SVM-CNN model achieves 87% accuracy in training and 91% accuracy in testing for road defect classification, showcasing its efficiency in pavement maintenance and management. The system presents the potential to significantly enhance the efficiency of road maintenance processes, making it a valuable asset for developing nations striving for a more streamlined approach to road network preservation.

Corresponding Author:

Rajesh Gujar
Department of Civil Engineering, Pandit Deendayal Energy University
Raisan 382 426, Gandhinagar, India
Email: rajesh.gujat@sot.pdpu.ac.in

1. INTRODUCTION

The development of infrastructure facilities and utilities has witnessed a significant surge in developing nations over the past few decades [1]. With over a century of growth, highways have evolved into major global transportation routes [2]. The transportation sector, a pivotal component of the infrastructure chain, profoundly influences the socioeconomic growth of regions and countries [3]. Roadway transportation plays a central role in daily life and the economy, providing mobility and contributing to production [4]. A well-maintained road network is crucial for socioeconomic progress, serving as a fundamental accelerator for civilization [5]. Within the domain of essential infrastructure asset management, the availability of a well-kept road network is essential to meet user needs and minimize issues arising from poorly maintained roads [6].

Maintenance considerations are particularly crucial, given the escalating population growth and economic development, leading to an increase in vehicles and traffic accidents [7]. The resulting increase in traffic load inevitably leads to pavement damage [8], imposing increased costs on the public and subsequently higher rehabilitation expenses [9]. Deteriorated pavement conditions adversely affect ride quality, create hazardous driving conditions, and contribute to vehicle damage, costing drivers approximately £2.8 billion annually [9].

Despite substantial expenditures on public infrastructure construction, road maintenance remains neglected in numerous developing countries, where emphasis on maintaining existing roads is deemed more desirable than constructing new ones [10], [11]. Neglect of short-term routine maintenance can result in general degradation and potentially severe failures, necessitating major maintenance work that may cost up to ten times more than proper preventative maintenance [12].

To address these challenges, pavement maintenance and management systems (PMMS) have been adopted by developed nations, focusing on optimal fund utilization for efficient repair and maintenance of specific road stretches [13]. Given the significant financial commitment involved in road construction, proper maintenance of these assets is essential. The level of maintenance significantly impacts the cost and safety and comfort of road users [13]. In the planning of pavement maintenance, an initial evaluation of the pavement status is essential [14]. Detecting and identifying defects in road surfaces are critical steps in maintaining the road network. Efficient roadway monitoring strategies aid engineers in recognizing developing distresses early, allowing for proactive maintenance planning [15]. Traditionally, trained officials conduct manual pavement monitoring, a method prone to inaccuracies, hazards, and inefficiencies [16]. The proposed research seeks to address these challenges by introducing an artificial intelligence (AI) approach for pavement defect detection.

While various methods exist for pavement distress identification, such as manual detection, sensor-based methods, smartphone sensor-based methods, and remote sensing methods, each has its limitations [17]. Sensor and smartphone sensor-based methods, for instance, lack precision when identifying specific types of distress. Remote sensing methods, while accurate, present drawbacks like high data acquisition costs and inflexibility [18]. AI, widely adopted across diverse fields, offers a promising solution for pavement defect detection. The proposed research leverages AI to achieve error-free, faster, and budget-friendly results.

The study represents a significant leap forward in pavement maintenance and management by focusing on a novel group of defects, namely alligator cracks, edge breaking cracks, longitudinal cracks, potholes, raveling, transverse cracks. Unlike previous works, the research introduces an innovative defect classification system that expands the understanding of pavement distress. Adding to its uniqueness, the dataset underpinning this investigation is meticulously collected by the authors, further elevating the novelty and reliability of the study. At the core of this research is the pioneering application of machine learning (ML) algorithms, featuring a distinctive combination of support vector machine (SVM) and convolutional neural network (CNN). This synergistic SVM-CNN model, not only enhances precision but also demonstrates a groundbreaking improvement in efficiency during road defect classification. This novel approach deviates from conventional methods, highlighting the forward-thinking nature of this research and its potential to redefine the landscape of pavement distress detection. In addition to introducing a novel defect group and employing an original dataset, this study contributes significantly by addressing a critical gap in the literature. Previous works have overlooked the combinational consideration of prominent defects of alligator cracks, edge breaking cracks, longitudinal cracks, potholes, raveling, transverse cracks, and current research fills this void. The results underscore the effectiveness of the SVM-CNN model in pavement maintenance and management, offering promising insights for substantial enhancements in the efficiency of road maintenance processes. This research holds particular significance for developing nations aiming for a more streamlined and effective approach to road network preservation, showcasing the potential for transformative advancements in the field i.e., collaboration of SVM-CNN which has not been adopted byresearchers previously.

2. BACKGROUND

Researchers are motivated to overcome current obstacles in pavement condition analysis, aiming for accurate, low-cost, and efficient assessment of pavement problems [19]. To address this challenge, various studies have been conducted, each presenting distinct methods. These studies aim to provide state-of-the-art insights into this research problem.

2.1. Machine learning approaches

Nejad and Zakeri [20] proposes an expert system for pavement distress classification using a radon neural network based on wavelet transform. The system utilizes wavelet modulus and radon transform for scale invariant feature extraction where the wavelet modulus is calculated, and radon transform is applied to the wavelet modulus. Experimental results demonstrate that the proposed expert system is effective for pavement distress classification, with advantages of being rapid, easy to operate, and having a simple structure, reporting a 94.41% accuracy rate [20]. Nejad and Zakeri [21] compares the discriminating power of multi-resolution texture analysis techniques (wavelet, ridgelet, and curvelet-based texture descriptors) for distress detection and isolation in asphalt pavement. Curvelet-based signatures outperform all other techniques for pothole distress whereas, ridgelet-based signatures outperform all other techniques for cracking distress [21]. Moussa and Hussain [22] suggested a technique for detecting and classifying pavement cracks based on graph cut segmentation and SVM [22]. Authors reported that the predicted crack quantifications were similar to field measurements at a 95% confidence level and 97.1% accuracy for crack-type categorization [22]. In another research [23], the researchers proposed an approach by developing a fully convolutional U-Net-based architecture to classify surface cracks that use a patch-based training procedure to allow limited datasets [23]. This work addresses the challenge of automating the annotation task for surface crack segmentation, which traditionally requires manual labeling by trained experts. Authors propose a fully convolutional U-Net based architecture for semantic segmentation of surface cracks, achieving state-of-the-art results in two different crack datasets [23]. A technique that touches 90% accuracy was developed using K-nearest neighbor (KNN) to segregate the type of pavement distress [24]. Ibrahim *et al.* [24] utilizes image processing techniques such as image thresholding, median filter, image erosion, and image filling. Two features, delta_x and delta_y, representing the length of pavement cracking in the x and y coordinate system, are computed. The computed features are fed to a KNN classifier to classify the pavement cracking into transverse and longitudinal types [24]. Praticò [25] aims to address the lack of methods and systems that can identify concealed cracks, particularly bottom-up cracks, in road pavements and monitor their growth over time and can be used to identify and classify differently cracked road pavements. The study proposes a supervised ML-based method for the identification and classification of the structural health status (SHS) of road pavements based on their vibro-acoustic signature. Different ML classifiers such as multilayer perceptron (MLP), CNN, random forest classifier (RFC), and support vector classifier (SVC) were used and compared, showing high accuracy in associating a specific vibro-acoustic signature to a differently cracked road pavement [25]. For MLP, CNN, RFC, and SVC, the accuracy was obtained as 91.8%, 95.6%, 95.6%, and 91.0%, respectively [25]. An innovative technique using artificial neural network (ANN), SVM, and KNN was developed. It was noted that SVM achieves significantly high accuracy compared to KNN [26]. For example, different ML algorithms, such as CNN, long term-short term (LSTM) networks, and reservoir computing models, were applied to distinguish the pothole on the road surface automatically [27]. Regional-based CNN has been proven effective in distinguishing the type of crack with considerable accuracy [28].

2.2. SVM and CNN approaches

Faudzi [29] developed an intelligent system using deep convolutional neural network (DCNN) to detect cracks on asphalt pavement. The study collected pavement crack images from online sources and developed their own dataset. The images were pre-processed, and small patches were extracted for input to the DCNN model and the model was trained and tested using different patch sizes, training algorithms, and architectures to determine the best classification. Performance evaluation was done in terms of accuracy, precision, recall, and F1-score. The proposed DCNN model proved to be robust and reliable compared to previously developed methods, providing good classification performance [29]. CrackU-net, a DCNN, is proposed for pixelwise pavement crack detection, outperforming traditional methods and other CNN-based methods [30]. Huyan *et al.* [30] claimed that CrackU-net can extract crack information from diverse types and qualities of pavement images and avoids false-positive crack detection. However, the research does not explore the generalizability of the CrackU-net model to different pavement types or crack severities, which could impact its applicability in real-world scenarios [30]. Zhu *et al.* [31] presents a vision-based method for bridge defects detection using transfer learning and CNNs. The transfer learning model is trained on 1,180 images and tested on 134 images taken from different bridges. The proposed approach achieved an accuracy of 97.8% for the testing set, demonstrating better performance in accuracy and efficiency compared to classical ML algorithms and hand-craft methods; however, the study focuses on the classification and identification of partial defects on the bridge surface, leaving room for future research to expand the range of the image classifier [31].

Gavilán *et al.* [32] proposes a fully automatic approach using a linear SVM-based classifier ensemble to distinguish between different types of pavements, with optimal feature vectors including texture-based features. Gavilán *et al.* [32] presents an adaptive road distress detection system that involves fully automatic road distress assessment using line scan cameras, laser illumination, and acquisition HW-SW (hardware and software). Pre-processing techniques are applied to smooth the texture and enhance linear features, while non-crack features detection is used to mask areas with joints, sealed cracks, and white painting to reduce false positive cracking [32]. A block-based and image-based classification technique using SVM was developed by [33] that classifies the patch and non-patch areas of the road surface. The patch area quantification has a percent absolute error of 11.04%, suggesting potential inaccuracies in the measurement. The system uses road surface video frames acquired by a smartphone or an external camera, positioned inside and outside of a moving passenger vehicle [33]. The system utilizes low-cost imaging technologies and SVM classification for identifying and measuring pavement patch areas in road surface video frames. The technique achieved 87.3% and 82.5% accuracy for block-based and image-based approaches, respectively [33].

Ersoz *et al.* [34] introduces a unmanned aerial vehicle (UAV)-based system using image processing and ML to monitor rigid pavements' conditions by identifying cracks. The system employs image processing for crack detection and segmentation, extracting geometric properties to train a SVM for classification [34]. While offering a cost-effective alternative to truck-based monitoring, the system may face challenges with shadowy or low-resolution images. Notably, it specifically addresses crack identification in rigid pavements, lacking coverage on other distress types like potholes, rutting, and raveling [34]. Sari *et al.* [35] explores an automated approach for classifying and segmenting asphalt pavement cracks, utilizing the SVM and OTSU algorithms. The SVM algorithm is employed for crack classification, while the OTSU algorithm is applied for crack segmentation. The study asserts the superior effectiveness and strength of the OTSU algorithm compared to traditional segmentation algorithms [35]. It was observed that UAV and ML provide a higher accuracy rate.

3. METHOD

In order to execute the research, the research was carried out in following steps: (i) data collection, (ii) data cleaning, (iii) data pre-processing and analysis, (v) data visalisation, and (v) model development through training and testing. Data collection: as shown in Figure 1, the data was collected from various stretches of the study area, i.e., Ahmedabad city. In order to collect and record the data; instruments such as data record sheets (for recording the following information: date, location, section, distress types, severity levels, quantities), hand measuring tape and streight ruler was used. The road stretches were selected per the defects' presence and the traffic flow. The selected road stretches are Iskon-Nehrunagar, Shilaj-Thol, Gita Mandir-Kalupur, CTM-Ishanpur, and Vasna-Paldi. The total length of the considered road stretch is 35 km as shown in Figure 2.

Figure 1. Adopted research methodology

All of the study sites were constrained to flexible pavements only. From the preliminary survey and according to IRC: 82-2015 code of practice for maintaining bituminous road surfaces (first revision) for flexible pavements, two categories, cracks and disintegration, out of four main categories, are focused on. The distress considered for data collection covers alligator cracks, edge breaking cracks, longitudinal cracks, potholes, raveling, transverse cracks. The data was collected via videos and photos using a smartphone device. The camera has a quad camera setup, which includes a 64-megapixel 1/1.7-inch sensor with f/1.9 aperture, an 8-megapixel ultra-wide sensor, and dual 2-megapixel sensors for depth and macro. A general camera is used to increase the cost-effectiveness of the system. Videos were captured for each defect from different road stretches. High-quality photos are also collected from google images as data to increase the versatility of the system. For the extraction of the images from the videos, OpenCV is used. A capture rate of 0.5 is chosen. If the duration of the video is 20 seconds, 40 images can be achieved in .jpg format. Each captured image is added to the data, and it is to be counted as +1. Completion of the above stage leads to the pre-processing of data.

Data cleaning: the data needs to be cleaned by pre-processing to make the information machine-friendly. Other than that, the dataset should symbolize certain quality and quantity standards. A relevant and well-balanced data set results in well-ordered and rapid training. Data pre-processing: for pre-processing, TensorFlow, and Keras are imported. The use of Keras not only makes the model robust but also saves much memory. In addition, TensorFlow provides a collection of workflows to develop, and train models using Python. Finally, rescaling, shearing, zooming, flipping, and resizing are performed with a batch of 32 to complete the pre-processing successfully. At the end of this stage, for training, 1,000, and testing, 100 images are collected as shown in Table 1.

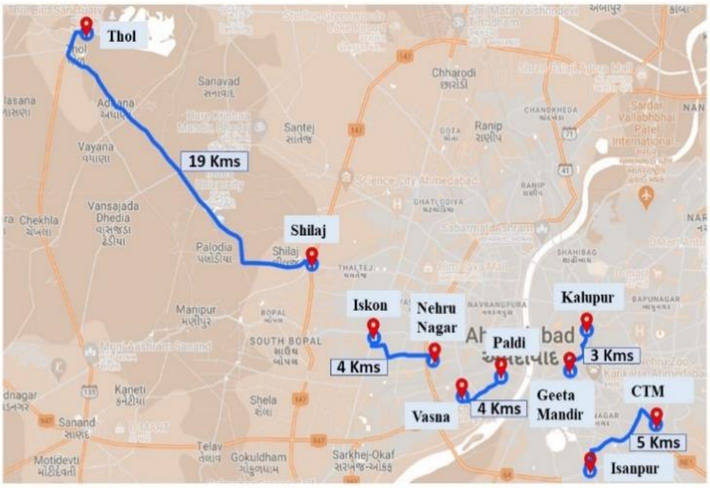

Figure 2. Details of study area

Table 1. Details of dataset

Classes	Number of samples in training	Number of samples in testing
Alligator crack	1,000	100
Edge breaking crack	1,000	100
Longitudinal crack	1,000	100
Potholes disintegration	1,000	100
Raveling disintegration	1,000	100
Transverse crack	1,000	100

Model training: the training images are ready and fed to the training model. The rectified linear activation function (ReLU) has been used for training. ReLU is a piecewise linear function and converges six times faster than the Tan h and Sigmoid activation functions in practice. It deactivates the negative neurons and keeps the machine focused on positive ones. To execute the SVM-CNN hybrid model for image processing, four steps are performed which are graphically represented in the Figure 3.

- Step-1: convolution operation: using all the kernel functions, padding, activation function ReLU, and stride of 2, the output matrix is generated for the image of 100×100×3.
- Step-2 pooling: the primary function of the pooling layer is to decrease the size of the matrix 2×2 matrix is result because of the given stride of 2. Using the max-pooling process, the 5×5 matrix is reduced to a 2×2 matrix. The max-pooling helps the machine to make decisions without confusion.
- Step-3 fully connected layers: all the previous inputs are connected and multiplied to give output. It is the final layer of CNN. L2 regularization is used for the selection and interpretation of features. SVM best suits the activation function SoftMax used in this layer. 50 epochs are applied. It means that each image is trained 50 times.
- Step-4 compiling with SVM: the model is compiled using Adam optimizer and square-hinge loss. Adam optimizer contributes to the easy understanding and configuration of features. Square-hinge loss provides the maximum possible loss by squaring the actual value of the loss.

Model testing: as the training steps are completed, the performance of the model is tested. As shown in Figure 4; for the SVM-CNN sequential model testing, an image is given to it, and it is expected to classify the defect. Cv2, Keras, and TensorFlow are used to pre-process inputted images. The images are resized to

(100, 100) and rescaled from 0 to 255. The NumPy library performs array operations on the image and expands the image's dimensions. After pre-processing the image of the defect that needs to be identified, the machine generates an output matrix by sequential convolutional and pooling layers. The model tries to match the resultant matrix with the training matrixes. The class of the maximum matching matrix is shown as a result.

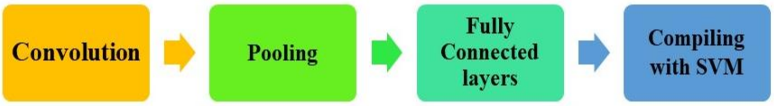

Figure 3. Steps adopted for SVM-CNN hybrid model

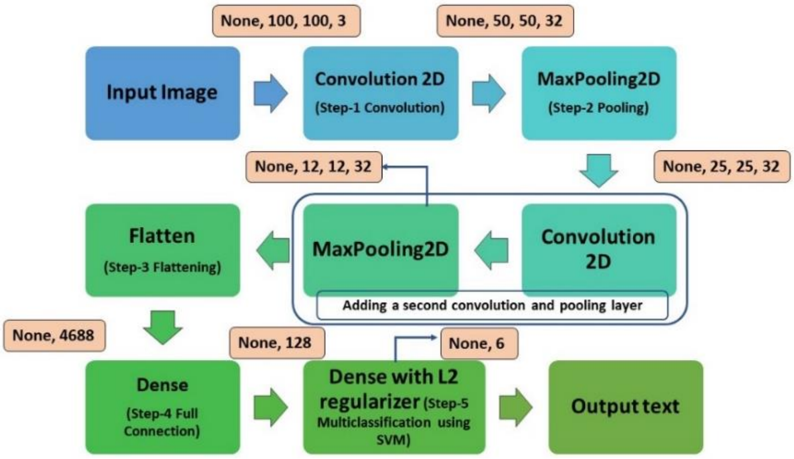

Figure 4. SVM-CNN model

4. RESULTS AND DISCUSSION

For this research, an SVM-CNN model was generated. The model consists of 2 convolutional layers, 2 pooling layers, one flattens layer and a dense layer. Different libraries are used for effective training and testing purposes. Cv2, TensorFlow, Matplotlib, Keras, and NumPy are used for feature extraction and interpretation. In this part of the paper, results are presented and discussed. The Figures 5 and 6 are the graphical representation of the training accuracy and testing accuracy respectively. Therefore, by using the developed model, the below results are obtained. The Table 2 shows that the SVM-CNN model is 87% accurate for training and 90% accurate for testing.

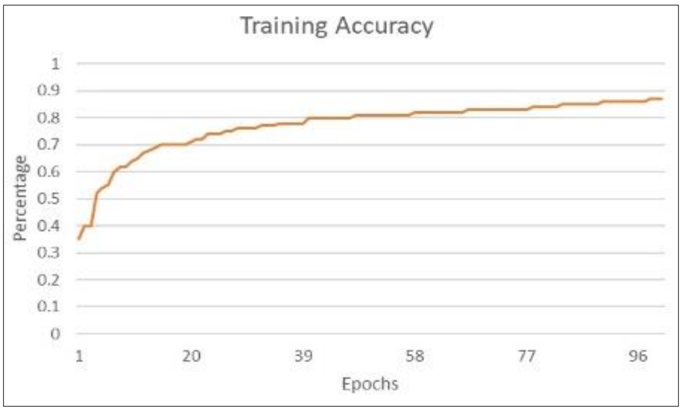

Figure 5. Training accuracy

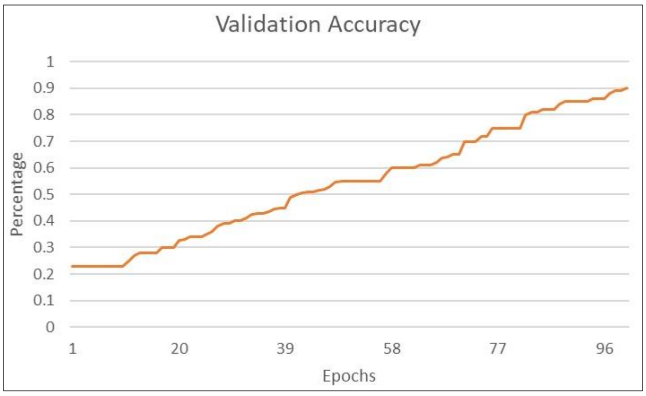

Figure 6. Testing accuracy

Table 2. Results

Name of content	Training	Testing
Number of classes	6	6
Number of samples	6	6
Number of samples per class	6,000	600
Accuracy	1,000	100
	87%	90%

5. CONCLUSION AND FUTURE SCOPE

In this study, the SVM-CNN model was developed for the accurate detection of flexible pavement defects i.e., alligator crack, edge-breaking crack, longitudinal crack, transverse crack, potholes, and ravelling disintegration class, achieving a commendable testing accuracy of 90%. The training process involved considering a 100×100 image size for enhanced resolution, with the inclusion of two convolutional layers and the use of L2(0.01) Kernel regularizer to address overfitting. The model demonstrated practical utility by allowing real-time testing through smartphone-captured images, providing prompt outcomes for cracks and disintegration. This research offers a comprehensive deployment of a ML-based model for roadway surface monitoring. Specifically, the CNN component showcased over 85% accuracy in testing and proved efficient in image processing for defect detection. The proposed model can assist in pavement maintenance decisions by detecting conditions, making predictions, and aiding resource allocation in pavement management systems. Future research can explore additional pavement deficiencies not covered in this study, aiming to improve accuracy and versatility. Optimizing the training process and addressing challenges like varied lighting conditions could contribute to model robustness.

ACKNOWLEDGMENTS

Without the exceptional help of Mr. P R Patelia (Chief Engineer (State) and Special Secretary, Roads and Building Department, Government of Gujarat) and his team, this study would not have been possible. Their zeal, expertise, and meticulous attention to detail have been an inspiration and have kept the work on track from the first draft to the final version of this paper.

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BIOGRAPHIES OF AUTHORS

Jaykumar Soni is research scholar in Civil Engineering Department, Pandit Deendayal Energy University, India. He Holds an M.Tech. degree in Infrastructure Engineering and Management specialization in Transportation Engineering. His research areas are pavement maintenance, placement defect detection, pavement management system. He has presented more than 30 research papers in various national and international conferences and is a recipient of different national and international awards such as best paper presentation award at Hi-Tech i-SOlutions LLP Competition, Indian Institute of Management –Ahmedabad (IIM-A). He can be contacted at email: jay.sphd19@sot.pdpu.ac.in.

Dr. Rajesh Gujar is currently an Assistant Professor in the Civil Engineering Department at the School of Technology, Pandit Deendayal Energy University. He holds a Ph.D. in Transportation Engineering from Sardar Vallabhbhai National Institute of Technology, Surat, earned in 2016. Additionally, he completed his M.E. in Construction Engineering and Management from B.V.M. Engineering College, S.P. University V.V. Nagar, Anand, in 1999, and his B.E. in Civil-Water Management from S.G.G.S.C.E. and T, Nanded (M.S), Dr. B.A.Marathwada University, Aurangabad (M.S.), in 1997. He has an extensive educational background and is affiliated with institutions such as S.V. National Institute of Technology, Surat, CEPT University, and Lamar University, Beaumont, Texas, USA. He has received recognition for his contributions, including being awarded for the "Best Performance in Public Works Department in Akola Municipal Corporation, Akola (Maharashtra)." He has an impressive publication record with numerous articles, chapters, and conference papers. Notable publications include articles in prestigious journals such as "International Journal of Construction Management," "Journal of The Institution of Engineers (India): Series A," and "Materials Today Proceedings." His research spans various topics, including sustainable road maintenance, application of machine learning techniques in transportation projects, and the utilization of alternative materials in construction. He has presented his work at conferences and has actively contributed to the academic community. He can be contacted at email: rajesh.gujar@sot.pdpu.ac.in.