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Department of Civil Engineering

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>>HOD's Message

I am happy to learn that the Department of Civil Engineering SAINTGITS College of Engineering is coming out with a technical magazine published by Civil Engineering faculty. I congratulate the editorial team for their excellent teamwork for shaping the magazine. I wish them all the best.

Dr. Susan Rose

Head of Department

Vision

Emerge as centre of excellence in Civil Engineering education.

Mission

- Develop Civil Engineers with commendable knowledge, innovative ideas and leadership qualities; who can appropriate technology and contribute efficiently to the industry and research.

PROGRAMME EDUCATIONAL OBJECTIVES(PEOS)

PEO1: To prepare graduates to satisfy the requirements of their employers for professional practice in Civil Engineering thereby serving the needs of society and profession.

PEO2: To prepare graduates to take up post graduate studies/research.

PEO3: To prepare graduates for professional advancement and business leadership.

PROGRAMME OUTCOMES (PO)

PO1: Apply knowledge of mathematics, science and civil engineering.

PO2: Identify, formulate and analysecivil engineering problems.

PO3: Design solutions for complex civil engineering problems and design system component or processes that meet the desired needs of the society such as public, health, and safety, cultural, societal and environmentalconsiderations.

PO4: Investigate and conduct experiments as well as to analyse and interpret data for complex civilengineering problems and come out with feasible solutions.

PO5:Create, select and apply appropriate techniques, resource and modern engineering tools necessary forcivil engineering practice considering limitations

PO6: Apply reasoning informed by knowledge to contemporary issues and the consequent responsibilities relevant to the professionalengineering practice.

PO7: Assess the impact of the engineering solutions in societal and environmental contexts for sustainabledevelopment.

PO8: Follow ethical principles andcommit to professional ethics and responsibilities and norms of the engineering practice.

PO9:Function effectively as an individual and as a member or leader in multidisciplinary teams.

PO10: Communicate effectively on complex Civil Engineering activities with the Engineering community and the society, being able to make effective presentations, write effective reports and design documentation.

PO11: Practice the engineering and management principles and to apply these principles to manage projects in multidisciplinary environments.

PO12: Engage in independent and life long learning

PAVEMENT CONDITION INDEXING USING YOLO ALGORITHM

Kalyani Nair, Krishnanayan S, Krishnendu B,Pretheuma S and Susan Rose

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Pavement maintenance is crucial for ensuring the longevity, safety, and cost-effectiveness of our roadways and infrastructure. Regular upkeep, such as repairing cracks, potholes, rutting, and applying protective sealants, prevents further deterioration caused by weather and traffic. Neglecting pavement maintenance can lead to costly repairs, reduced road safety, and increased traffic congestion. Therefore, prioritizing pavement maintenance is essential for the sustainability and functionality of our transportation networks. Pavement Condition Indexing is a crucial element in effectively managing road infrastructure, facilitating the timely recognition and prioritization of maintenance requirements. It involves assigning a numerical value to a pavement based on visual inspections, evaluating the extent and severity of distresses like cracks and deterioration. This numerical representation encapsulates the overall health of the pavement, allowing authorities to systematically identify areas in need of urgent maintenance. Pavement distress detection plays a pivotal role in the condition rating of roads. Timely detection enables efficient scheduling of maintenance interventions, reducing repair costs and minimizing traffic disruptions. Manual methods rely heavily on human inspection, making them time-consuming and prone to subjectivity, leading to inconsistent results. You Only Look Once (YOLO) is a deep learning model used for object detection. It excels in real-time object detection, especially for smaller objects, making it a preferred choice for various applications, including road pavement distress detection. The model is trained to identify predominantly potholes, raveling and edge cracking which is interpreted using a user interface system. The result of the interface system displays the number of pavement distresses along with their areas according to which ranking of roads is done using AHP analysis. Pavement condition indexing done by this method is beneficial to prioritize the maintenance of roads.

Keywords: Pavement maintenance, Distress Detection, YOLOv8, AHP

General Background

Pavements play a vital role in our daily lives, serving as the foundation for transportation infrastructure. Whether it is roads, highways, runways, or parking lots, pavements enable the smooth movement of people and goods. However, over time, pavements are subjected to various environmental and mechanical stresses, resulting in wear and tear.

Pavement maintenance is critical for ensuring the longevity, safety, and functionality of the pavements. It offers an economical, safe, and preservation-focused way to deal with problems like cracks, potholes, and uneven surfaces. Regular maintenance also improves an area's aesthetic appeal, which boosts property values and tourism. It also improves traffic flow, aligns with sustainability goals, reduces liability risks, and aids in asset management. Frequent upkeep can greatly increase the lifespan of pavement, postponing expensive reconstruction. Furthermore, it contributes to public satisfaction, increasing support for infrastructure investments and improving overall quality of life.

Pavement condition indexing is a critical aspect of road infrastructure management, aiding in the timely identification and prioritization of maintenance needs. It is a numerical value based on visual inspections and assessments of pavement distresses that represents the overall condition of a pavement.

The most crucial step in road distress detection is a visual inspection of the pavement and expert evaluation. This method is costly, time-consuming, and frequently results in unreliable and inconsistent results. Inspectors are also exposed to highway operations. Various attempts have been made to develop automated devices for pavement damage detection and detection in order to overcome the limitations of visual inspection methods. In fact, this new system provides non-contextual, efficient, and accurate data, allowing for a thorough analysis of pavement conditions

Several distress identification catalogues developed by various researchers and organizations use nearly identical identification and evaluation criteria. The ASTM D6433-16, which provides distress criteria identification and classification for both flexible and rigid pavement, is one of the most well-known and widely used references.

Alternative methods for pavement distress detection include pavement condition surveys, acoustic sensors, laser profilers, moisture and density testing, ultrasonic Testing, deflection testing and deep learning approaches. These methods provide objective and datadriven assessments of pavement conditions, allowing for more accurate and effective pavement maintenance and management. Surveys use specialized vehicles, sensors, cameras, and data collection systems to capture data on pavement conditions, including cracks, potholes, rutting, and surface roughness. Acoustic sensors detect sound or vibrations produced by traffic passing over the pavement, while laser profilers create detailed profiles for surface distress detection. Pavement distress detection using deep learning involves training convolutional neural networks (CNNs) on large datasets of pavement images or sensor data. These models automatically identify distresses, such as cracks and potholes, with high accuracy, reducing the need for manual inspections. The advantages include automation, accuracy, scalability, consistency, and potential for real-time monitoring, but challenges include the need for large labelled datasets and computational resources. Deep learning approaches hold great promise for enhancing pavement distress detection and improving maintenance management.

YOLOv8 is a deep learning model that uses the Darknet-53 network model, consisting of 53 convolutional layers and 23 residual layers. The model employs 1x1, 3x3/2, and 3x3 convolution kernels to extract image features, ensuring exceptional performance in object detection and classification. The other layers ensure optimal convergence of the detection model. It combines three feature maps of different scales to detect different parts of the same object simultaneously. In the training phase, the image is partitioned into $S \times S$ grids, with each grid forecasting whether the center of the object of interest is inside it. If the grid predicts B detection bounding boxes and Conf (Object), the candidate box confidence for the non-existence of a target is imposed to zero. Each detection bounding box has parameters such as position, height, width, and Pr(Classi|Object) probability of C categorizes.

To carry out a preventive maintenance strategy for an entire road network, detailed information about current road conditions must be available. This can only be obtained through precise distress identification and classification. Maintenance authorities can strategically allocate resources to promptly address issues such as cracks, potholes, and rutting by identifying and classifying them. Pavement condition rating can aid to prioritize the rehabilitation and maintenance work by providing the severity of the present condition of the pavements. In addition to ensuring the pavement's longevity and safety, early intervention through targeted maintenance reduces the overall cost, disruptions, and annoyances to the public associated with reactive repairs.

Literature Review and Summary

Recent advancements have shown that deep learning and image processing can significantly improve pavement distress detection. Pan et al. (2020) developed a method using the YOLO network to detect and classify pavement distresses. Their approach, which analyzed a large dataset of distress images, achieved a detection accuracy of 73.64% and processed images at lightning speed—0.0347 seconds per image. This method's robustness across different lighting conditions makes it a powerful tool in real-world applications.

Abbas et al. (2021) introduced a novel, cost-effective technique for automated pavement distress detection. Their method, which achieved an accuracy of 88.44% compared to manual methods, underscores the practical benefits of using image processing for real-time pavement evaluation. Mandal et al. (2020) tested deep learning algorithms in diverse geographical locations, including Japan, the Czech Republic, and India. Using the YOLO framework, they achieved impressive F1 scores, outperforming other models like CenterNet and EfficientDet. This study highlights the global applicability and effectiveness of deep learning in detecting pavement distresses. Parla et al. (2022) focused on creating an affordable yet accurate system for detecting and measuring pavement distresses. By using the YOLOv8 algorithm and low-cost detection devices, they achieved detection rates ranging from 91.0% to 97.3%. This method, validated with data from urban roads in Italy, demonstrated the potential for comprehensive road inspections using accessible technology and artificial intelligence.

Innovative approaches are also being explored for assessing pavement conditions and prioritizing maintenance. Buttlar et al. (2021) developed an asphalt pavement condition index using deep machine learning. By training models on a large dataset of pavement images from Google Street View, they were able to detect and quantify various types of pavement distress. Their system, validated on six pavement sections, demonstrated robust predictions of the Pavement Surface Evaluation and Rating (PASER), showing the power of machine learning in pavement assessment.

Sreh et al. (2022) utilized machine learning algorithms to predict the Pavement Condition Index (PCI). Comparing Random Forest (RF) and Support Vector Machine (SVM) models with traditional regression methods, they found that RF and SVM offered high prediction accuracy, with R^2 values of 99.7% and 96.8%, respectively. This study highlights the potential of machine learning to accurately predict pavement conditions.

Nautiyal et al. (2022) used the Analytic Hierarchy Process (AHP) to prioritize maintenance for low-volume rural roads in India. By considering factors like pavement distress, traffic volume, and socioeconomic facilities, they developed a systematic approach for road maintenance prioritization. Their methodology, validated in Himachal Pradesh, proved effective for managing rural road networks. Kresnanto (2022) also applied AHP to road maintenance prioritization in Indonesia, focusing on various criteria and sub-criteria. By interviewing road maintenance experts and using the Likert scale, they established traffic volume as the most critical factor, followed by road condition, policy, economic factors, and land use. This structured approach provided a comprehensive method for prioritizing road maintenance, aiding in efficient resource allocation.These studies collectively illustrate the significant advancements in pavement distress detection and assessment technologies. From deep learning and image processing to machine learning and AHP, these innovative approaches are paving the way for more accurate, efficient, and cost-effective solutions in pavement maintenance and management.

Methodology

In this comprehensive road infrastructure management approach, the focus is on identifying low-volume roads characterized by rutting, edge failure, and raveling as predominant distress types. The methodology begins with the acquisition of pavement distress datasets from available sources and selected pavements. A crucial step involves data preprocessing to ensure the quality and relevance of the datasets. Subsequently, a YOLOv8 model is trained using Python on an i7 system to accurately identify distress types, particularly rutting, edge failure, and raveling. Following successful training, the model is tested to validate its proficiency in distress identification. Distress intensity estimation is then performed to gauge the severity of identified distress types. The process proceeds to Pavement Condition Indexing (PCI) using AHP, incorporating distress data into a quantitative measure that informs maintenance prioritization. Installation of the program on an i7 system allows for continuous monitoring, ensuring ongoing assessment of pavement conditions. Documentation and maintenance practices are implemented to record findings and facilitate adaptive strategies. In summary, this method integrates machine learning, distress intensity estimation, and PCI for a holistic approach to road asset management, providing an efficient and systematic way to monitor, as.

Data Collection

Initially, low volume roads were identified for the purpose of obtaining pavement distresses and its condition rating. Distresses were classified according to ASTM D6433-16. The main distresses which were focused were edge cracking, raveling, rutting and potholes. Datasets of pavement distresses were obtained from GAPS dataset and CRACK500 dataset available online.

The datasets from the low volume roads are geotagged images, which also implies the type of distresses found on that particular latitude and longitude. In the process of collecting and labeling datasets, the Roboflow platform has been utilized. The annotations primarily categorize the dataset into three distinct classes: low, medium, and high. These classes are associated with the severity levels of various road defects, namely raveling, edge cracking, and potholes. The use of such detailed class labels allows for a nuanced understanding of the dataset, enabling the development of machine learning models capable of discerning and categorizing the severity of road anomalies. This level of granularity is crucial for the accurate identification and assessment of road conditions, facilitating the implementation of effective solutions and maintenance strategies.

Roboflow is a comprehensive platform designed to simplify the complex process of managing and preparing image datasets for machine learning models, particularly those focused on computer vision tasks. While it is not solely a dedicated annotation tool, it provides a range of functionalities that include annotation, preprocessing, and augmentation. One of its key features is the availability of annotation tools, allowing users to label objects within images. These tools support different annotation formats such as COCO, Pascal VOC, and YOLO, providing flexibility for various computer vision workflows.

Training YOLOv8 Model

Google Colab, a cloud-based platform, was leveraged to train the YOLO v8 model for pavement distress detection. This choice of platform offers several advantages, including access to powerful GPUs and TPUs, which expedite the training process, especially for deep learning models like YOLO. By utilizing Google Colab, the computational burden is shifted to the cloud, enabling users to train complex models without the need for high-end hardware.

The input dataset for this project was sourced from the labeled image dataset provided by Roboflow. This dataset contains annotated images depicting various types of pavement distress, such as potholes, raveling, and edge failure. These distress types were further classified into three severity levels: low, medium, and high. The availability of a well-annotated dataset is crucial for training accurate machine learning models, as it provides the necessary ground truth labels for supervised learning.

The YOLO v8 model, renowned for its real-time object detection capabilities, was chosen for its efficiency and accuracy in detecting pavement distress. YOLO (You Only Look Once) models excel in detecting objects in images swiftly and accurately by dividing the image into a grid and predicting bounding boxes and class probabilities for each grid cell. This approach enables YOLO to achieve impressive detection speeds without compromising accuracy.

During training, the YOLO v8 model was fed 1120 images, each with dimensions of 640x640 pixels. The choice of image resolution is critical, as it balances between computational efficiency and the model's ability to capture fine-grained details in the images. By providing a sizable dataset with consistent image dimensions, the model learns to generalize well across various pavement distress scenarios and scales.

After training the model on the dataset, an evaluation was conducted to assess its performance. The evaluation metrics used typically include precision, recall, and accuracy. In this case, the total accuracy achieved by the YOLO v8 model for pavement distress detection was measured at 78.7%. This metric indicates the model's overall ability to correctly identify pavement distress instances across the dataset. While achieving high accuracy is desirable, it's essential to consider the model's performance across different distress types and severity levels to ensure robustness in real-world applications.

The system was ensured with the access to a GPU by selecting the appropriate runtime type and verified GPU setup using the nvidia-smi command. Ultralytics and YOLOv8 dependencies were installed using pip install command. The YOLOv8 model was imported from Ultralytics.

With a dataset comprising 1120 images of dimensions 640x640 pixels and a total accuracy of 78.7%, the trained model demonstrates promising results in identifying potholes, raveling, and edge failure across various severity levels. This underscores the potential of deep learning models in automating pavement condition assessment tasks, paving the way for more efficient and cost-effective infrastructure maintenance strategies.

Development of User Interface

React.js was selected as the framework for developing the user interface for pavement distress analysis, specifically targeting potholes, raveling, and edge break. Leveraging React.js offers numerous advantages for this application, including its component-based architecture, which facilitates modular development and reusability of code. This allows for the creation of a dynamic and responsive user interface that can efficiently handle the complexity of uploading multiple images simultaneously. Through React.js, users can seamlessly upload up to 100 test images at a time, streamlining the process and enhancing user experience. The interface guides users through the uploading process, ensuring smooth navigation and intuitive interaction.

Once the images are uploaded, React.js manages the integration with the pavement distress analysis algorithm, orchestrating the processing of each image to identify and categorize potholes, raveling, and edge break. The framework's state management capabilities enable real-time updates, keeping users informed about the progress of the analysis. Upon completion, React.js presents a comprehensive report detailing the number and type of pavement distresses detected in each uploaded image, along with their respective areas. This report is presented in a clear and visually appealing format, enhancing readability and understanding.

Additionally, React.js facilitates seamless integration with other technologies and libraries, enabling the incorporation of advanced features such as image processing and visualization tools to enhance the analysis and reporting capabilities further. Overall, by leveraging React.js for the user interface development of pavement distress analysis, the application can provide a streamlined, efficient, and user-friendly experience for analyzing pavement conditions and generating insightful reports to aid in maintenance and decision-making processes.The interface for pavement distress analysis leveraging React.js has been meticulously crafted to ensure a smooth and intuitive user experience. At its core, React.js enables the creation of reusable UI components that can be composed together to form complex interfaces. For this application, the development process likely began with the identification of key components necessary for the upload and analysis workflow.

Firstly, a file upload component was implemented to allow users to select and upload multiple images simultaneously. React.js simplifies the handling of file uploads, providing mechanisms for monitoring upload progress and handling errors gracefully. This component likely includes features such as drag-and-drop functionality and progress indicators to enhance usability.Once the images are uploaded, React.js manages the interaction with the pavement distress analysis algorithm. This involves sending the uploaded images to the backend server for processing and receiving the analysis results. React.js facilitates this communication through HTTP requests, enabling seamless integration with the backend API.During the analysis process, React.js updates the interface dynamically to provide feedback to the user. This may include displaying progress indicators, such as a loading spinner, to indicate that analysis is in progress. Real-time updates are also provided to inform the user when the analysis is complete and the report is ready for viewing.

The interface for viewing the analysis report is another crucial component developed using React.js. This component likely presents the analysis results in a clear and organized manner, with visualizations and charts to enhance understanding. React.js makes it easy to manage the state of the report interface, enabling dynamic updates based on user interactions or changes in the analysis data.
Throughout the development process, React.js promotes code reusability and maintainability, allowing developers to create modular UI components that can be easily extended or modified as needed. This results in a flexible and robust interface that can adapt to future requirements and enhancements.

Analytical Hierarchy Process

Saaty (1980) introduced the Analytical Hierarchy Process (AHP) as a robust tool for managing both qualitative and quantitative factors in decision-making. AHP organizes criteria hierarchically, making it inclusive for multi-criteria decision-making. The process involves several steps. Initially, a hierarchical structure of the problem is created. Then, each level of the hierarchy is assigned a nominal value, followed by pairwise comparisons using a questionnaire distributed to relevant stakeholders such as managers or experts. Each decision maker evaluates the relative importance of each pair of criteria. Individual judgments are then aggregated into group judgments using geometric averaging. The scale used for comparison ranges from one to nine, representing equality to extreme importance. In the next step, priority eigenvalue matrices are derived for criteria and sub-criteria separately, followed by the formulation of weightage matrices. Finally, the ranking of options is determined by generating a Global Priority Vector.

Determination of Priority Values

Priority values for the formation of paired comparison matrix were derived secondarily from expert opinions. Table 5.1 provided below shows the priority values assigned to different criteria and sub-criteria. Example: If the two factors considered for the prioritization of roads for maintenance are raveling and pothole, which factor would you prefer and how much important is that factor than the other one? (Please note: If you prefer a value of '8' for pothole by pair-wise comparison over raveling, you may choose the option ' p 8 ‘. Here ' r ' stands for raveling and ' p ' stands for pothole.)

Table 5.1 Priority Values from Response Sheet

Factors	Minimum Priority Values from Experts	Maximum Priority Values from Experts	Mean Priority Values from Experts
Raveling and Pothole	7	9	p7
Raveling and Edge Break	2	4	r2
Pothole and Edge Break	6	7	p8

Priority Vectors

The normalized principal eigenvector, also known as the priority vector, is derived by averaging across the rows. As it is normalized, the sum of all elements in the priority vector equals 1.

This vector illustrates the relative weights among the items being compared. In the Analytic Hierarchy Process (AHP), priority vectors are obtained through the principal eigenvalue method (EM). The priority vector for criteria such as traffic, lack of drainage, and distress was formulated through the following steps. Firstly, a matrix was created based on the comparisons between these criteria, resulting in a 3x3 matrix. The diagonal elements of this matrix were set to one. Then, the upper triangular matrix was filled following these guidelines:

- If the judgment value was less than 1, the actual judgment value was used.
- If the judgment value was greater than 1, the reciprocal value was utilized.

The following steps has been followed:

1.Formulation of the paired comparison matrix:

$$
\begin{array}{c} \\ P \\ R \\ E \end{array}
\begin{array}{c}
\begin{array}{ccc} P & R & E \end{array} \\
\begin{pmatrix} 1 & 7 & 8 \\ 1/7 & 1 & 7 \\ 1/8 & 1/7 & 1 \end{pmatrix}
\end{array}
$$

2. Sum of reciprocal matrix of each column:

$$
\begin{array}{c|ccc}
 & P & R & E \\
\hline
P & 1 & 7 & 8 \\
R & 1/7 & 1 & 7 \\
E & 1/8 & 1/7 & 1 \\
\Sigma & 71/56 & 57/7 & 16
\end{array}
$$

3. Matrix obtained by dividing each element with sum of its column, which will be the normalized relative weight. The sum of each column will be 1

$$
\begin{array}{c} \\ P \\ R \\ E \end{array}
\begin{array}{c}
\begin{array}{ccc} P & R & E \end{array} \\
\begin{pmatrix} 56/71 & 49/57 & 1/2 \\ 8/71 & 7/57 & 7/16 \\ 7/71 & 1/57 & 1/16 \end{pmatrix}
\end{array}
$$

4. The normalized eigen vector can be obtained by averaging across the rows. The weightage for severity of distress is mentioned in table 5.2. The obtained priority vector for various types of distresses is mentioned below.

Potholes = 0.716

Raveling= 0.22

Edge Break= 0.06

Table 5.2 Weightage for severity of distress

Distress	Weightage (%) for severity of distress		
	Low	Medium	High
Raveling%	30	70	100

Pothole%	70	85	100
Edge break%	70	80	100

Source: Pavement Performance Modelling and Calibration of HDM-4 Deterioration Models for Rural Roads in India: -B S Mathew

Pavement Condition Indexing

The condition assessment of pavements involves evaluating the distress observed across ten different pavement sections. For this purpose, images capturing the pavement distresses are taken over a length of 250 meters. The various types of pavement distresses identified in these images are then quantified by calculating their respective areas. These areas are weighted using priority vectors, which have been formulated to reflect the relative importance or severity of each type of distress.

By summing these weighted areas, the total distress area for each pavement section is determined. This total distress area is then used to calculate the distress percentage, representing the proportion of the pavement affected by the identified distresses. Based on these distress percentages, a ranking system is developed to prioritize the pavements, facilitating maintenance and repair decision-making processes. This method ensures a systematic and objective approach to pavement condition indexing, allowing for effective resource allocation and improved pavement management.

Table 6.11 shows the prioritization order of the road sections considered.

Table 6.11 Total Priority

S.No	Roads	Total Priority	Ranking
1	Arakunnam- Olipuram	12.86	6
2	Pepathy- Vattapara	5.1	8
3	Chethipuzha-Kurichy	51.78	2
4	Vattapara- Veliyanadu	33.16	3
5	Vakathanam Pallikadavu	18.36	5
6	Muringanattupara	20.2	4
7	Chethipuzha- Parathumpara	9.51	7
8	Pathamuttom	3.31	10
9	Kaippattoor- Cherukara	95.27	1
10	Edakkatuvayil- Arayankavu	3.93	9

From the obtained ranking of roads, Kaippattoor- Cherukara road requires significant maintenance to prevent further deterioration.

Results

A pavement distress detection model integrated with a user interface system has been developed, utilizing the YOLOv8 algorithm for object detection. The model achieved an accuracy of 78.7%, demonstrating its effectiveness in identifying pavement distress. Subsequently, a priority ranking system was implemented for each road, allowing for the determination of the prioritization order of various road stretches based on their condition. AHP analysis was used for the prioritization of pavements. This comprehensive approach facilitates efficient maintenance planning and resource allocation, ensuring that the most critical areas receive attention first. The ranking of roads according to the chronological order of their priority is shown in Table 7.1.

Table 7.1: Ranking of Roads

S.No	Name of Road	Ranking
1	Pathanmuttom	10
2	Edakkatuvayil- Arayankavu	9
3	Pepathy- Vattapara	8

4	Chethipuzha- Parathumpara	7
5	Arakunnam- Olipuram	6
6	Vakathanam Pallikadavu	5
7	Muringanattupara	4
8	Vattapara- Veliyanadu	3
9	Chethipuzha-Kurichy	2
10	Kaippattoor- Cherukara	1

The user interface system for the pavement distress detection model was developed using React.js, providing an intuitive and interactive platform for users. This interface allows users to efficiently identify and analyze pavement distress, displaying the number and type of detected distresses along with their corresponding areas. The interface features a visually appealing and user-friendly design, ensuring ease of navigation and accessibility. Users can view detailed information about each detected distress, including categorization and spatial distribution, which aids in comprehensive pavement condition assessments. By leveraging the capabilities of React.js, the system ensures a seamless and responsive user experience, facilitating effective decision-making for pavement maintenance and management.

The Analytical Hierarchy Process (AHP) has proven to be highly effective in the decision-making process for prioritizing low volume roads. This method's objective nature ensures that discrepancies are minimized, thereby providing a more dependable framework for future studies. By systematically evaluating various criteria and alternatives, AHP offers a structured approach that enhances the reliability and consistency of prioritization decisions. This makes it an invaluable tool for planners and engineers, facilitating informed decision-making and optimizing resource allocation in infrastructure development projects. The robustness of AHP in reducing subjective bias further underscores its utility in producing replicable and transparent outcomes, which are essential for long-term strategic planning and policy formulation in the realm of transportation infrastructure.

Conclusion

In conclusion, this project holds paramount importance in addressing the critical aspects of pavement maintenance and infrastructure management. The longevity, safety, and cost-effectiveness of our roadways hinge on the timely identification and prioritization of maintenance needs. The developed You Only Look Once (YOLOv8) deep learning model for object detection, focusing on pavement distresses like cracks, potholes, and rutting, represents a cutting-edge solution to enhance the efficiency and accuracy of distress detection. Grounded in the Pavement Condition Indexing (PCI) system, which provides a numerical representation of pavement health through visual inspections and severity assessments, our model contributes significantly to the systematic evaluation of infrastructure conditions.

Traditional manual methods for distress detection often fall short due to their time-consuming nature and susceptibility to subjectivity, leading to inconsistent results. By leveraging YOLOv8, known for its real-time object detection capabilities and proficiency in handling smaller objects, our model aims to overcome these limitations, providing a more reliable and efficient approach to pavement distress detection. The real-time capabilities of YOLOv8 not only improve accuracy but also contribute to the prompt scheduling of maintenance interventions, reducing repair costs, and minimizing traffic disruptions.

The utilization of annotated datasets has proven to be pivotal in enhancing the clarity of observations within the realm of distress identification. Through meticulous selection and fine-tuning of a pre-trained YOLOv8 model, the accurate identification of distress patterns has been achieved. Subsequent refinement through techniques such as non-maximum suppression has further improved the precision of distress recognition, culminating in a commendable accuracy rate of 78.7%. The integration of a user interface developed in JavaScript, seamlessly interfacing with the Python-based machine learning components, enables efficient interpretation of distress types and their respective areas. Furthermore, the quantification of pavement distress has been methodically undertaken through the analytical hierarchy process, where eigenvalues have been assigned to distinct distress categories—0.716 for potholes, 0.22 for ravelling, and 0.06 for edge breaking—providing a structured approach to evaluating pavement conditions. Moving forward, the pavement condition indexing is slated for completion utilizing AHP analysis, thus ensuring a comprehensive assessment framework for infrastructure maintenance and planning.

The numerical rating system allows for a more nuanced and precise prioritization of maintenance efforts, ensuring that resources are allocated where they are most needed. In essence, this project offers a sophisticated and practical tool for the sustainable management of transportation networks, promoting infrastructure longevity and overall road safety.

The future scope of a Pavement Distress Detection and Rating project employing YOLO involves multifaceted advancements. To begin with, there is room for the enhancement of real-time monitoring capabilities, allowing for immediate responses to emerging pavement issues. This could be achieved by integrating advanced sensors and cameras to ensure continuous, up-to-date data collection. Accuracy improvement remains a key focus, necessitating ongoing research to fine-tune YOLO models, diversify datasets, and incorporate additional deep learning techniques. Integration with maintenance systems is crucial, as the project could seamlessly generate work orders or notifications for road maintenance crews based on the severity and location of detected distress.

Depth cameras hold significant potential for the efficient detection of potholes. The accuracy and reliability of these detection models can be substantially improved by augmenting the training process with larger and more diverse datasets. Furthermore, integrating Geographic Information Systems (GIS) with these detection models will enable real-time identification and mapping of pavement distresses. This GIS integration can facilitate timely maintenance and repair, enhancing road safety and reducing long-term infrastructure costs. By leveraging advanced imaging technology and comprehensive spatial analysis, these innovations promise to revolutionize the field of pavement condition monitoring and management.

VEHICLE ACTUATED TRAFFIC SIGNAL USING AI

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ABSTRACT

Traffic congestion in urban areas leads to capacity issues, intersection delays, increased congestion, fuel consumption, and air pollution. Advanced traffic management systems, including adaptive signals and intelligent transportation systems, offer solutions to mitigate congestion and improve road network efficiency. Utilizing live camera imagery and AI for real-time traffic density assessment, alongside adaptive signal control algorithms, reduces congestion and optimizes traffic flow, aligning with the trend of technology-driven transportation systems for environmental benefits. YOLO (You Only Look Once) is a renowned AI object detection algorithm, enabling a vehicle-activated traffic signal to adjust timing based on traffic density, reducing congestion, wait times, and pollution. A simulation and prototype demonstrate the proposed system's effectiveness compared to fixed-time signals. It dynamically adjusts green signal durations based on traffic density, prioritizing high- traffic directions to minimize delays, congestion, and fuel consumption. Results show significant improvements in vehicles crossing intersections, with potential enhancements through real-world data calibration. Leveraging existing CCTV infrastructure, the system reduces deployment and maintenance costs compared to other intelligent traffic control systems. Integrating into major cities can enhance traffic management, with future features like traffic rule violation detection, accident identification, signal synchronization, and emergency vehicle adaptation, offering comprehensive traffic flow and safety solutions.

1 Introduction

The escalating volume of vehicles in urban environments presents a pressing challenge for road networks, manifesting in reduced road capacity and a declining level of service. A significant contributor to traffic issues is the reliance on fixed signal timers at intersections, which lack adaptability to fluctuating traffic demands. Consequently, there is a growing imperative for innovative traffic control solutions under the domain of Intelligent Transport Systems. Presently, three primary traffic control methods are employed: manual controlling, conventional traffic lights with static timers, and electronic sensors. Manual control, though effective, demands a considerable workforce, rendering it impractical for comprehensive coverage across urban areas. Static timers fail to respond dynamically to real-time traffic conditions, while electronic sensors, despite their advancement, encounter challenges in accuracy, coverage, and cost-effectiveness. These limitations underscore the need for more sophisticated and budget-friendly solutions to address the evolving complexities of urban traffic management. The implementation of Smart Traffic Signal Control using AI, specifically integrating the You Only Look Once (YOLO) algorithm, serves multiple objectives with significant potential for improving urban traffic management. The system aims to enhance real-time traffic monitoring and response by efficiently detecting and classifying various vehicle types at junctions, allowing for dynamic signal timing adjustments based on traffic density to optimize vehicle flow and alleviate congestion. Additionally, it strives to contribute to environmental sustainability by minimizing fuel consumption and reducing emissions through traffic flow optimization, aligning with broader sustainable development goals. Moreover, the implementation seeks to establish a scalable and adaptable framework, enabling continuous learning and adaptation to changing traffic patterns, ensuring its long-term effectiveness in addressing the evolving needs of urban transportation. In recent years, the widespread use of video monitoring and surveillance systems in traffic management has become prominent, serving various purposes such as security and real-time information provision to travelers. These systems enable the estimation of traffic density and vehicle classification, offering opportunities for optimizing traffic flow and reducing congestion by adjusting traffic signal timers dynamically. This study aims to develop a traffic light controller, specifically designed to adapt to real time traffic conditions. By utilizing live footage from CCTV cameras at intersections, the system assesses real-time traffic density and adjusts the duration of green signals as needed, employing YOLO to precisely identify and categorize vehicles. The primary objective is to optimize green signal times to facilitate faster traffic clearance compared to static systems, thereby reducing delays, congestion, and waiting times, ultimately contributing to decreased fuel consumption and pollution.

2 Literature review

Early studies focused on optimizing signal timing through computer simulations, emphasizing the need for effective calculations of signal split and cycle lengths. One such study by Webster [1] used a combination of approximation formulas to calculate the average delay per vehicle, suggesting that adjusting green time allocation based on the highest flow-to-saturation-flow ratio could significantly reduce delays at signalized intersections. This approach provided a framework for understanding how variations in signal timing affect overall intersection capacity and has influenced subsequent research on adaptive signal systems. These early efforts laid the foundation for the growing use of adaptive and technology-driven systems that have become a central focus of more recent studies.

As traffic systems became more complex, researchers turned to fixed-time traffic signal coordination, where the optimization of traffic flow became more intertwined with real-time data and simulations. In [2] an analytical model with a coevolutionary transport simulation is integrated to improve the coordination of fixed-time signals in real-world scenarios. The coupling of these models allowed for more effective synchronization of signals across large-scale networks, offering advantages over traditional signal systems. Their findings revealed that optimized fixed-time signals outperformed other methods by improving traffic flow and reducing congestion, highlighting the effectiveness of combining both theoretical models and real-time traffic simulations in large urban settings. This approach represents a significant step forward in ensuring that traffic management solutions can scale and adapt to the dynamic needs of modern cities.

Further advancements in traffic management have leveraged more affordable and accessible technologies, such as microcontroller-based systems. Another study demonstrated [3] how Arduino-based systems, utilizing infrared (IR) sensors, could dynamically adjust signal timing based on real-time vehicle detection. This low-cost solution provided a practical and adaptable alternative to traditional traffic signal control, allowing for adjustments to green light durations based on the volume of traffic detected at each phase. These systems proved to be particularly useful in localized or smaller-scale deployments, offering flexibility in areas where deploying large-scale infrastructure would be cost-prohibitive. While these systems are effective in limited settings, the potential for integration with larger urban traffic control systems remains an area for further exploration.

While previous studies primarily focused on optimizing fixed-time signal coordination, real-time signal adjustments, and microcontroller-based systems for localized applications, they often overlooked the integration of AI-driven dynamic signal control with existing infrastructure or real-time traffic flow data. These studies provided significant advancements in traffic management but did not fully explore the potential of combining AI object detection with live camera feeds to adapt signal timings based on actual traffic conditions.

3 Methodology and Data Collection

Our proposed system uses images from CCTV cameras at intersections to perform traffic density calculations via image processing and object detection algorithm. Employing YOLO for vehicle detection, the algorithm identifies various vehicle classes such as cars, bikes, buses, autorickshaws and trucks, facilitating accurate traffic density assessment. The signal-switching algorithm then adjusts green signal timers for each lane based on this density and other relevant factors, updating red signal times accordingly. To prevent lane starvation, green signal times are constrained within maximum and minimum values. Through simulation and prototype development, the system's effectiveness is showcased and compared with the existing system.

3.1 Working of Traffic Signals in Real-Time

The process begins with cameras capturing real-time videos at intersections. The system employs image processing techniques to detect vehicles within the captured frames. Following vehicle detection, the next step involves calculating the traffic density based on the number of identified vehicles. Subsequently, the green signal time for traffic lights is determined, likely influenced by the calculated traffic density. Finally, the traffic signal timer is updated accordingly, reflecting the dynamically assessed conditions to optimize traffic flow at the intersection.

3.2 Methodology

The methodology involved several key steps. Firstly, the process began with the selection of a suitable site for the study. Subsequently, a comprehensive survey of traffic volume at this selected site was conducted. The dataset collection phase comprised two distinct aspects: gathering videos for algorithm development and obtaining images for training the YOLO model. After the video dataset collection, a simulation was created using pygame to mimic real-time traffic scenarios. Simultaneously, After YOLO training, a prototype was developed with Arduino. These steps ensured a robust foundation for algorithm development and training, incorporating both simulated and real-world data sources to enhance the system's effectiveness and accuracy.

3.2.1 Site Selection and Preliminary Survey

The chosen site for this study is S. H. Junction in Changanassery. The selection was based on the observation that certain vehicles experience delays in crossing the road, whereas wasted green time is observed on another road. To provide a visual reference, Figure 1 presents a typical photograph of SH Junction in Changanassery. A traffic volume survey was conducted at the specified junction to assess the flow of vehicles. The survey involved obtaining accurate traffic volume counts, allowing for a thorough analysis of the vehicular movement at the location. By converting the collected data into Passenger Car Units (PCU), a standardized measure that represents the traffic load of different vehicle types, a more meaningful understanding of the overall traffic dynamics was achieved. Additionally, the identification of peak hours provided crucial insights into the times of the day when traffic congestion is at its highest.

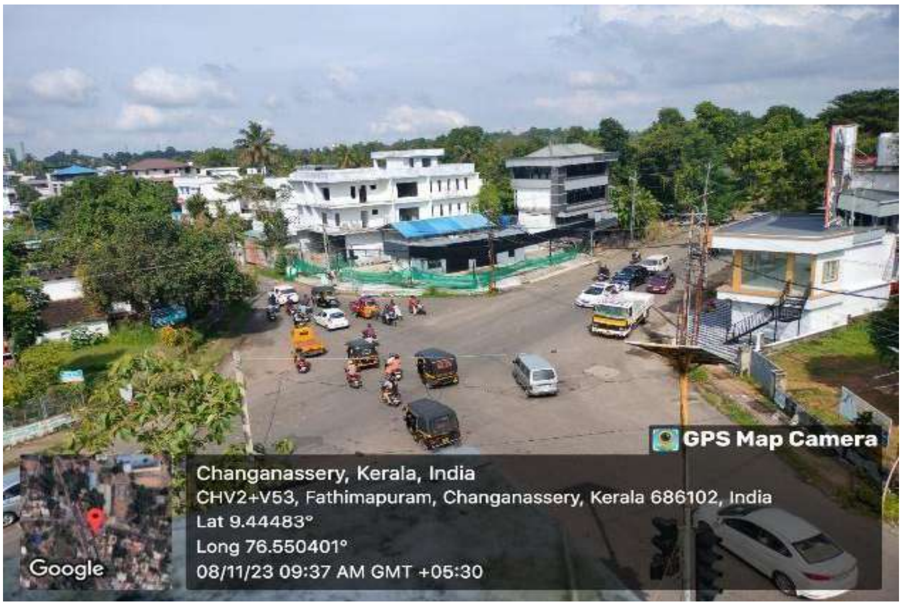

Figure 1. SH Junction, Changanaserry

3.2.2 Simulation Model

To develop a simulation using Pygame, real-time datasets were essential for an accurate representation of traffic dynamics. To capture relevant data, 10-minute-long videos were recorded at a specific intersection. Subsequently, the collected data was meticulously analyzed, with a focus on tabulating different values of waiting times and the number of vehicles waiting in queue after the signal time. This approach ensured that the simulation incorporated realistic scenarios, enhancing its applicability and reliability. The integration of real-time data into the simulation contributes to its authenticity. Pygame, a popular Python library for game development, was employed to create simulations based on the tabulated data. This versatile library provides a framework for interactive and visual applications, making it suitable for illustrating complex systems such as traffic scenarios. Leveraging the tabulated data, five simulations were developed to showcase both the existing and proposed traffic systems at a specified intersection. The simulations aimed to provide a comparative analysis, allowing to visually assess the performance and efficiency of the proposed traffic system approach in comparison with the current one. Each simulation ran for a total duration of 25 minutes, 300 seconds each, capturing snapshots of traffic patterns and dynamics in both scenarios. This simulation serves the purpose of visualizing the traffic system and comparing it to the existing static model. The simulated environment features a 4-way intersection equipped with four traffic signals. Each signal is accompanied by a timer, indicating the remaining time before the signal transitions. Additionally, each signal displays the count of vehicles that have traversed the intersection. Various types of vehicles, including cars, bikes, buses, trucks, and rickshaws, approach from all directions. To enhance realism, some vehicles in the rightmost lane execute turns as part of their traversal through the intersection.

3.2.3 Prototype development

Figure 2 illustrates the block diagram of an intelligent traffic control light system designed for a four-way traffic scenario. The key components include cameras, a microcontroller, a power supply, and a traffic light system. In contrast to the traditional traffic light system, which uniformly allocates the same time delay to all lanes irrespective of their traffic density, this smart system operates more efficiently. It determines the lengths of the green, yellow, and red-light phases based on the present traffic density. Utilizing YOLO and cameras, the system detects the presence of vehicles in any lane, transmitting this information (calculated density) to the microcontroller. Subsequently, the microcontroller appropriately configures the ON time for the green and red LEDs. Consequently, the timing of the traffic lights becomes contingent on the density of vehicles present in any of the four lanes, introducing a more responsive and intelligent traffic control approach.

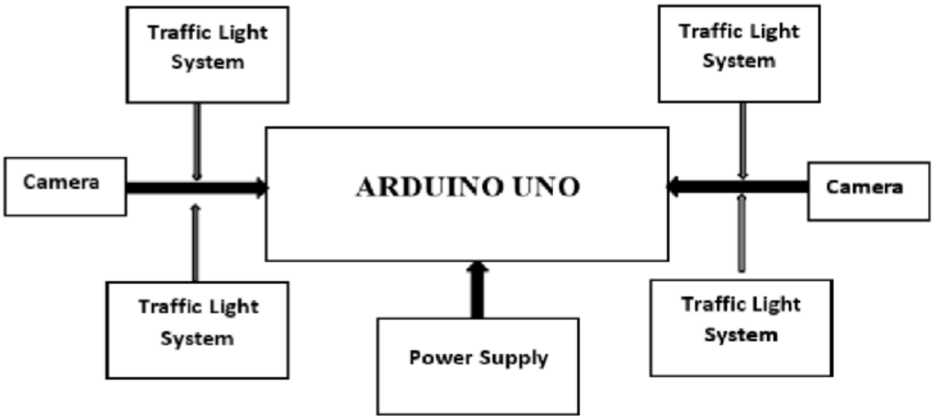

Fig 2 Block Diagram Of Prototype

4 Results and Discussions

Following a meticulous tally of vehicles in each direction, we identified peak hours by converting the counts into PCUs (passenger car units). Notably, during the 4:00 PM to 5:00 PM timeframe, the highest number of vehicles was recorded, marking this period as the peak hour for vehicular activity at the intersection. From the observations conducted during the volume survey, we derived a layout that is visually represented in Figure 3.

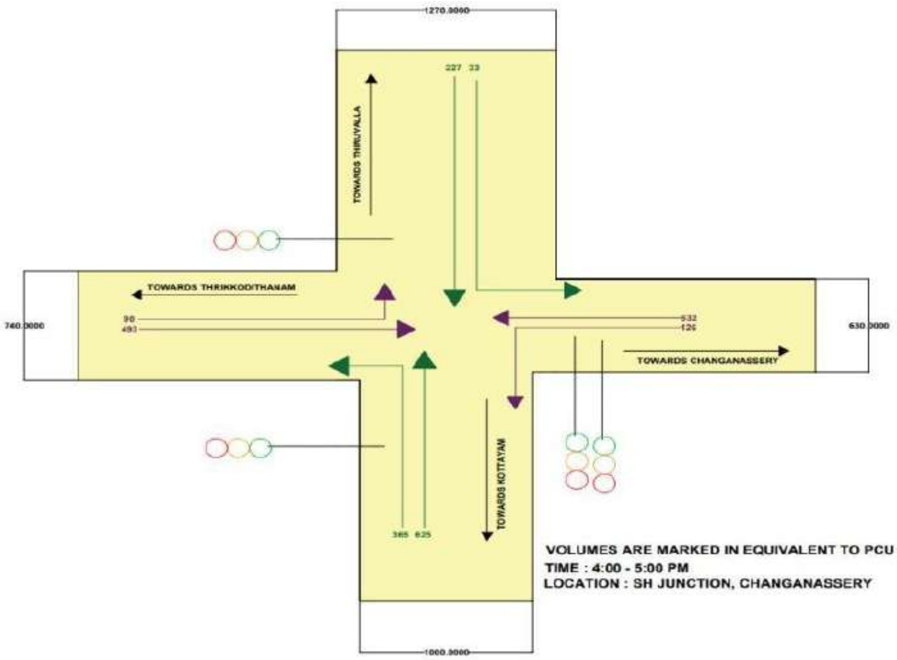

Figure 3. Layout of Intersection

4.1 Simulation Results

Collected data of 10 mins duration from videos were tabulated and upon examining the results, it becomes evident that in the Thrikkodithanam direction, not all vehicles manage to pass through the intersection during the green signal; there are some vehicles left behind. Conversely, in the other three directions—

Kottayam, Thiruvalla, and Changanassery—it is noted that the green signal time is not fully utilized, resulting in wasted time during which no vehicles pass through. A simulation was created using Pygame to replicate real-world traffic scenarios, aiding in the visualization and comparison of the system with the pre-existing static model. Figure 5 provides a snapshot of the conclusive result of this simulation. To evaluate and compare the performance of the current system with the proposed system, we conducted simulations using five different datasets. During these simulations, we focused on two key metrics to assess the efficiency of the traffic flow: the number of vehicles successfully passing through the Thrikkodithanam lane, and the waiting time experienced by vehicles in the other three lanes, namely Kottayam, Thiruvalla, and Changanassery. Figures 4 and 5show graphical representation of simulation results.

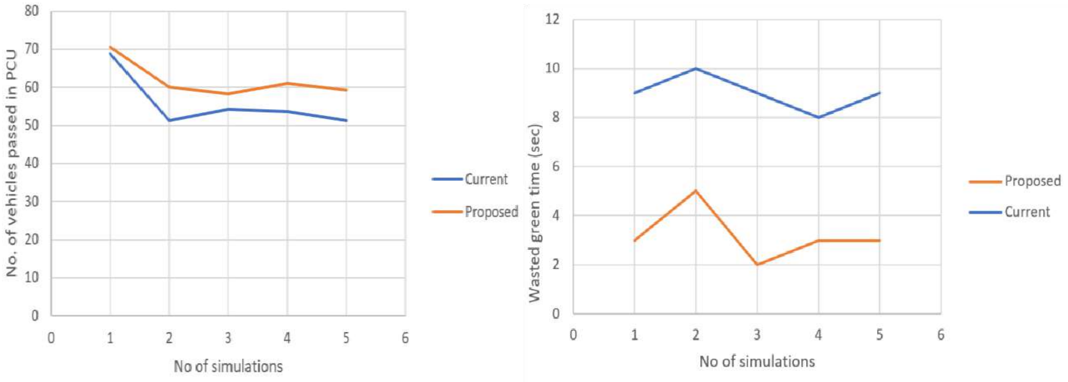

Figure 4. Comparison of the current system with the proposed system (Thrikkodithanam lane and Changanassery lane)

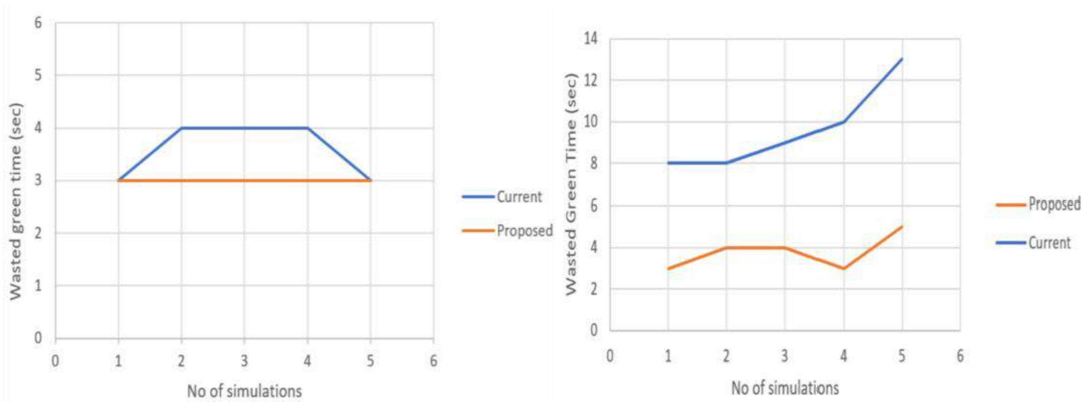

Figure 5. Comparison of the current system with the proposed system (Thiruvalla lane and Kottayam lane)

Our results demonstrate the effectiveness of using real-time video feeds for traffic simulations, providing a more accurate representation of traffic flow and congestion. This approach mirrors the methods described in [4], where real-time video feeds were used to estimate traffic bulkiness and congestion levels. In our work, we utilized video data to create simulations, enabling us to closely replicate real-world traffic patterns and evaluate the performance of our system.

Moreover, [5] addresses the need for adaptive traffic systems that can efficiently process and respond to real-time traffic data, highlighting the importance of using such data to improve traffic flow and reduce congestion. Similarly, our use of real-time video feeds for simulation demonstrates the potential of dynamic data, our simulation model was able to adapt to varying traffic conditions, allowing for more accurate traffic signal control and improved traffic flow management. This approach aligns with the growing emphasis on integrating real-time data into traffic systems for better efficiency and safety. Based on these results, it is clear that our proposed system is more efficient than the current system at the selected site. All five simulation outcomes consistently demonstrate this improvement.

4.2 Prototype of proposed system

A prototype was developed to demonstrate the operation of the traffic signal system. For testing purposes, several components were necessary, including an LED traffic light module to display red, yellow, and green lights, an Arduino microcontroller to run the code, male-female wires for connections, a breadboard for circuit prototyping, an Arduino adapter for powering the board, and a laptop for control and monitoring. In this system, two webcams are positioned on either side of the road, alongside four traffic lights. The Arduino microcontroller manages the cameras, tallying the number of vehicles as they pass through the road. Signal adjustments occur when the camera detects traffic congestion. The system operates in three distinct cases: Case 1 - If no vehicles are present on the road, the light stays red until vehicles arrive (Figure 6); Case 2 - If there is varying traffic density at signals, the system prioritizes the road with the highest density by turning the light green (Figure 7); and Case 3 - If all roads exhibit equal density, the system activates a sequential arrangement, allowing the lights to operate normally by controlling the signals one after the other.

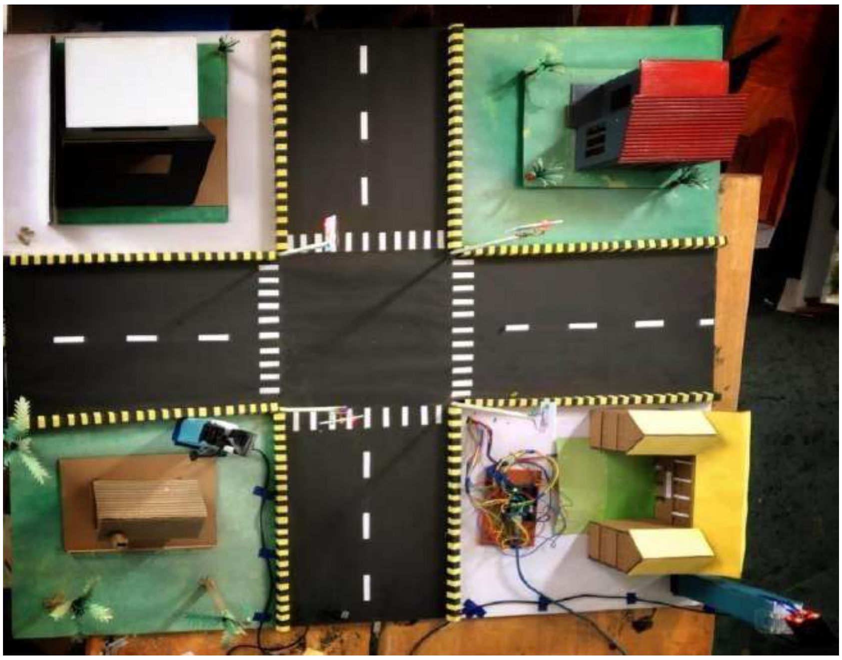

Figure 6. The practical smart traffic light system case 1

Figure 7. The practical smart traffic light system case 2

4.2.1 Testing

We conducted testing to evaluate the system and verify each of its functions, ensuring compliance with the required specifications. Four cases were covered, including: Initially, all traffic lights remain red until vehicles are detected. In instances of higher traffic density on a specific road, priority is given to turning the traffic light green for that road. When all roads exhibit equal density, the system activates a sequential arrangement between the roads. If two roads have identical density levels, priority is granted to turning the traffic light green for the road that experienced congestion first.

4.3 Proposed system in Changanassery

Maximum Green Time per Phase (G) = 35s
Lost Time per Phase (L) = 2s (typically used to account for the transition time or delays)
Amber Time per Phase (A) = 2s
Phase Duration = 35s + 2s + 2s = 39s
Total Cycle Time = 4 × 39s = 156 s
Thus, the maximum cycle time for the traffic signal, considering the given parameters, is calculated as 156 seconds for our site which currently is 120s.

Our study successfully integrated YOLO with CCTV cameras to enhance traffic management by dynamically adjusting signal phases based on real-time vehicle detection and traffic density. YOLO's ability to accurately detect vehicles in real-time makes it an ideal tool for adaptive traffic control. This is in line with the approach used in [6], which also utilized YOLO for optimizing traffic signal timings. The integration of YOLO with existing CCTV infrastructure in our system highlights its practicality for urban traffic management. This real-time detection enables efficient signal utilization, reducing congestion and improving road safety without the need for additional hardware. YOLO's power in vehicle detection and its ability to adapt signal phases based on traffic conditions proves its potential for transforming traffic management in smart cities.

5 Conclusions

In conclusion, the proposed system effectively improves traffic management by dynamically adjusting green signal durations based on real-time traffic density. By allocating longer green times to higher-traffic directions and minimizing delays for less-congested areas, it reduces waiting times, congestion, and fuel consumption, leading to lower pollution levels. Simulation results indicate a significant improvement over existing systems in terms of vehicle throughput. This adaptive approach, utilizing real-time video feeds, also offers practical advantages over current systems like pressure mats and infrared sensors. The system's minimal hardware requirements—leveraging existing CCTV cameras—reduce deployment and maintenance costs, making it a cost-effective solution for cities. Integration with real-time video data allows for adaptive signal adjustments based on traffic density, enhancing safety, traffic flow, and overall efficiency. The successful prototype implementation highlights the potential for future innovations in intelligent traffic management systems. Future work could focus on integrating features like detecting traffic violations, identifying accidents or breakdowns, synchronizing traffic signals, prioritizing emergency vehicles, and incorporating multi-modal transportation considerations. Moreover, further research could explore the potential integration of this system with applications like Google Maps, providing access to collected data for visualization and predictions.

6 Conflict of interest

The authors declare no conflicts of interest related to this research.

REFERENCES

[1] Webster,F.V. (1958)*Traffic Signal Settings. Transportation Research Board.* https://trid.trb.org/view/113579

[2] Thuniga, T., Scheffler, R., Strehler, M., Nagel, K. (2019). *Optimization and simulation of fixed-time traffic signal control in real-world application*. Procedia Computer Science, 151, 826-833. https://doi.org/10.1016/j.procs.2019.04.113

[3] Okpara, C., Oguchienti, S., Nwosu, K., Ogidi, I. (2020) *Design of a Smart Traffic Light Control System using Arduino Mega.* International Journal of Scientific & Engineering Research, 5(11), 1350-1352. https://www.academia.edu/download/92034207/Design- of-a-Smart-Traffic-Light-Control-System-using-Arduino-Mega.pdf

[4] Gupta, M., Miglania, H., Deo, P., Barhatte, A. (2023). *Real-time traffic control and monitoring*. e-Prime - Advances in Electrical Engineering, Electronics and Energy, 5(4), 100211. https://doi.org/10.1016/j.prime.2023.100211

[5] Sukhadia, A., Upadhyay, K., Gundeti, M., Shah, S., Shah, M. (2020). *Optimization of smart traffic governance using artificial intelligence*. Augmented Human Research, 5(13). https://link.springer.com/article/10.1007/s41133-020-00035-x

[6] Kunekar, P., Narule, Y., Mahajan, R., Mandlapure, S., Mehendale, E., Meshram, Y. (2023). *Traffic management system using YOLO Algorithm*. Engineering Proceedings, 59(1), 210. https://doi.org/10.3390/engproc2023059210

ANALYSIS AND DESIGN OF METAMATERIAL BLOCKS WITH SELF-SENSING CONCRETE

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Abstract. Concrete plays an important role in infrastructure that stand the test of time. Developing concrete materials with advanced functionalities and mechanical tunability is critical in reimagining the conventional infrastructure systems. A new lightweight composite metamaterial concrete with remarkable mechanical properties along with sensing functionalities is introduced. The proposed self-sensing metamaterial concrete system is developed by integrating mechanical metamaterial and carbon nanotube enhanced concrete, forming reinforcement auxetic polymer lattices fully embedded inside a conductive cement matrix.
Three patterns for polymer lattice are to be proposed as 3D drawings in the 'SolidWorks' software. The designs are intended to keep the concrete and lattice bonded in all possible loading conditions. Different polymers for lattice are analysed, considering their material properties and 3D printability. Most suitable design and material for lattice is to be finalised by ANSYS based validation procedure. Finalized design is 3D printed to form the mould.
Self-sensing concrete enhanced with MWCNT is incorporated into the lattice to form the metamaterial-concrete block. This induces contact-electrification between its layers under mechanical excitations. Furthermore, the sensing functionality of the concrete systems for health monitoring of large-scale concrete structures is explored. This system can be applied as building base isolators, machine vibration isolators, shock absorbent bike lane pavement and runway pavement to decelerate aircraft in short length. The metamaterial self-sensing concrete paradigm can enable design of smart infrastructure systems with advanced functionalities.

Keywords: Mechanical metamaterials, MWCNT, Self-Sensing Concrete, 3D Printing, Multifunctional, Self-Health Monitoring

1 Introduction

Concrete is one of the most used materials in the global construction industry, with almost 30 billion ton being produced annually, owing to its commendable attributes such as rapid development of compressive strength, ease of shaping, and a favorable cost-to-weight ratio. However, the material has significant long-term challenges post-construction, primarily stemming from its high brittleness and limited tensile strength and strain characteristics. To maintain the integrity of concrete structures, prioritizing structural health monitoring (SHM) is essential in safeguarding concrete components from degradation and failure [1]. To address these limitations and enhance the overall performance of concrete, extensive research efforts have been invested over the past decades. A major focus has been on developing new concrete that promise improved mechanical properties by incorporating conventional reinforcements in it [2][3][4]. Consequently, there has been considerable research focus in the past two decades on smart cementitious materials endowed with self-sensing capabilities [5]. Researchers have investigated integrating diverse conductive materials into cementitious matrices, such as carbon black [6][7], carbon fibers [8][9], carbon nanotubes [10], steel fibers [11], and other monolithic or hybrid conductive substances [12], to achieve self-sensing capability. The underlying objective shared by these investigations is to fundamentally alter the behavior of concrete to enhance its ductility. Ductility allows a material to deform plastically upon yielding while retaining functionality, contrast to brittle materials like concrete that fail abruptly upon reaching yield. Enhanced ductility significantly boosts the concrete's capacity to withstand various loading conditions, notably bending, compression, and tension, thereby improving its suitability for structural applications.

To further explore the arena of functional applications of concrete, the concept of multifunctional concrete composites has emerged as an area of interest. It can be a key aspect in the development of smart civil infrastructure systems owing to its scalability, cost-effectiveness, and self-sustainability by green energy harvesting. A mechanical metamaterial concrete design can profoundly improve the multifunctionality of conventional concrete. Mechanical metamaterials are synthetic materials characterized by engineered structures, with exceptional mechanical attributes. Lately, there has been a notable increase in the exploration of various aspects of mechanical metamaterials for engineering purposes. Our proposal focuses on analyzing and developing multifunctional mechanical metamaterial self-sensing concrete. We combine and introduce both mechanical metamaterials and concept of SHM into the concrete structures through a single composite. We rationally design the system as an arrangement of a polymer lattice incorporated self-sensing concrete matrix with a vision of adjustable buckling, self-recovery, and energy absorption capabilities. Metamaterials derive their defining characteristics from the intricate arrangement of subunits, affording extraordinary properties such as negative Poisson’s ratio (υ), elastic modulus (E) and compressibility, and a nearly zero shear modulus. The auxetic arrangement is intertwined with the residual geometry of the metamaterial, ensuring horizontal and vertical stability, as well as increased compressibility. Additionally, the embedded auxetic structure acts as reinforcement for the concrete. The concrete blend offers the necessary strength and rigidity for the composite metamaterial to be fully realized, while the residual geometry continues to connect with the auxetic configuration. In addition, the selected composite will be developed in beam form, to see if it fits as a structural member. This paper also explains the potential future developments and the expected practical applications of the proposed metamaterial self-sensing concrete system.

2 . Material Properties and Methods

2.1 Materials

Material Properties. Mechanical metamaterials are a class of materials engineered to exhibit unique and often counterintuitive mechanical properties due to their geometric arrangement. These materials are created by combining multiple elements, often using composites like metals and plastics. They are typically structured in repeating patterns at scales smaller than the wavelengths of the phenomena they affect. The design principle of the lattice involved, careful arrangement of unit cells at the micro or nanoscale, resulting in materials with properties not found in natural materials.

A comprehensive review was conducted to identify potential substitutes, focusing on critical properties such as thermal expansion, water resistance, and bonding efficacy with concrete. Among the materials considered, PETG (Polyethylene Terephthalate Glycol), PLA (Poly Lactic Acid) and TPU (Thermoplastic Poly Urethane) emerged as promising considerations owing to economic considerations and accessibility. Two material combinations involving PLA – TPU and PETG – TPU were finalised. The following Table 1 shows material properties of PLA and PETG elements.

Table 1. Material properties of PETG and PLA

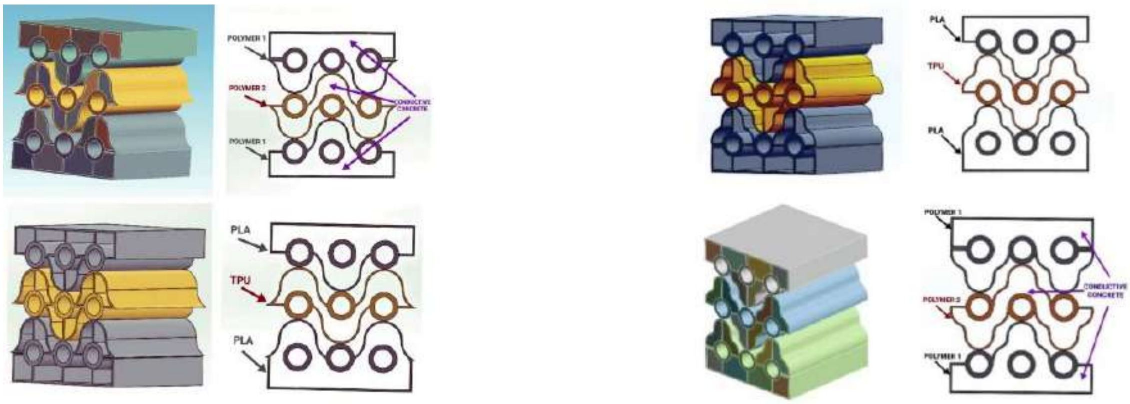
Material Property	PETG	PLA
Density	1.27 g/cm^3	1.25 g/cm^3
Young’s Modulus	1711 MPa	2350 MPa
Compressive strength	55 MPa	30 MPa
Poisson’s Ratio	0.38	0.30

Materials combinations for Analysis. Notably, three distinct materials were analysed for the lattice. Two combination models were analysed to fix the material for lattice where, in model 1 PLA is utilized for Part 1 and Part 3 of the model. PLA, a biodegradable thermoplastic, is known for its ease of use and environmental friendliness. Conversely, Part 2 of the model is crafted using TPU, indicating a deliberate selection of a different material for specific functional or mechanical properties. In model 2, PETG was utilized for Part 1 and Part 3 of the model. PETG is highly a recyclable filament, making it environmentally friendly. This choice was likely made based on considerations such as PETG is more flexible than PLA or ABS but still very strong and has a larger heat and water resistance. Conversely, Part 2 of the model was crafted using TPU.

Mix Proportion. The cement used for the experimentation was OPC 53. Before embarking on the design, a thorough analysis of preliminary experimental material properties was conducted. This analysis encompasses characteristics of materials such as cement and aggregates, providing essential data to form the subsequent mix design. Based on the assumed standard deviation and specifications in IS 10262:2019, mix design for M25 concrete mix was performed. Water cement ratio was taken as 0.475 and maximum size of coarse aggregate was limited to 6mm. 0.5% MWCNT was added to incorporate self-sensing behaviour in concrete.

2.2 Methodology

The validation of the proposed design stands as a pivotal phase in the research, crucial for ensuring the structural integrity and reliability of the innovative concept under a spectrum of diverse loading conditions. Recognizing the complexity of this task, ANSYS software-based validation process is employed. The analysis begins with the drawing of a three-dimensional model of the envisioned structure, a task undertaken with precision and detail using the SolidWorks software. Once the SolidWorks drawing was complete, ANSYS was employed for a comprehensive analysis. This validation procedure, pivotal for the finalization of the design, also includes the selection of an appropriate material for the polymer lattice, a decision crucial for the overall performance of the metamaterial concrete system.



(a) (b)

Fig. 1. Schematic diagram of 2 different unit cell models of metamaterial self-sensing concrete designed using SolidWorks. Fig. 1a. Model 1. Fig. 1b. Model 2

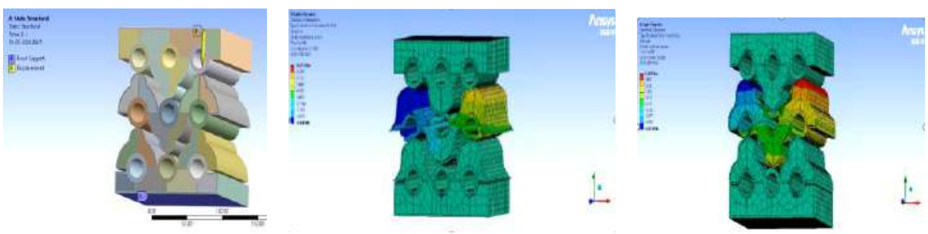
3 Analytical Methods

3.1 ANSYS Based Analysis

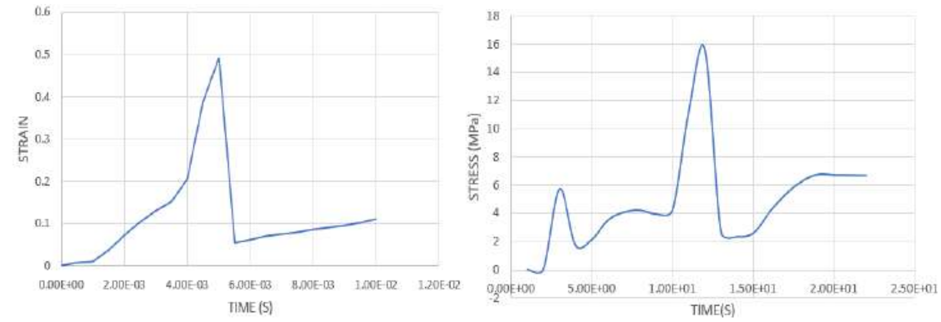
The validation process for fixing a design and material for the polymer lattice is done using the ANSYS software. The virtual 3D model for the validation process was created using SolidWorks software to replicate the physical system. For experimental testing, it was determined that using cubic dimensions would yield practical data on how the metamaterial behaves in terms of longitudinal displacement and its recovery after compression release. Hence, we standardized the lattice size to 150 mm × 150 mm × 150 mm for upcoming iterations of the designs. Two primary tests were conducted to assess the properties: cyclic compression and ultimate compression tests with a deformation velocity of 1.6mm/min.

The cyclic compression test help in understanding how the model behaves over time and its durability under cyclic loading conditions. On the other hand, the ultimate compression test provides crucial data regarding the pattern's strength and its ability to withstand extreme compressive forces. Both tests utilized sophisticated analysis systems, including static structural and explicit dynamics analysis. The analysis focused on several key parameters which provide insights into how different patterns deforms and responds to stress from different directions, helping in optimizing the design for maximum performance and durability.

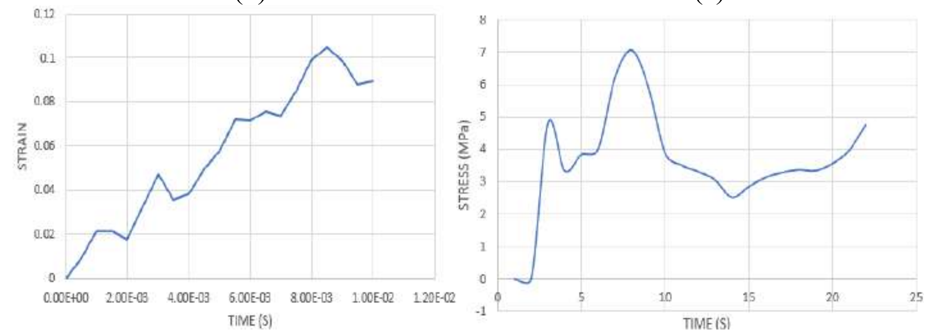
In case of model 1, The sudden drop in strain shown in Fig 2d. indicated localised failure, unpredictable behaviour under load and questionable geometry which may lead to performance issues and operational risks in dynamic environment. Whereas, model 2 exhibited minimum deflection while attaining maximum stress as shown in Fig 2c which indicated a favourable geometry. The result comparison between the finalised two models paved way for selection of model 2 (Fig. 2c) as the base model. Likewise, two different material combinations were also analysed in the base model (Fig. 3).



(a) (b) (c)

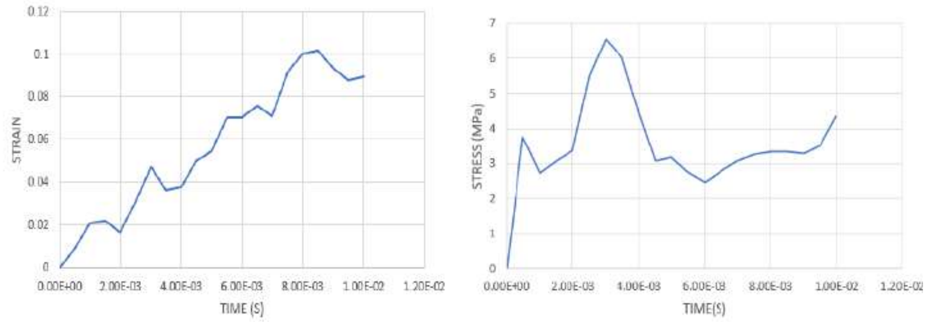


(d) (e)



(f) (g)

Fig. 2. Analysis outcomes of 2 different unit cell models using PLA and TPU. **Fig. 2a.** Loading conditions of the pattern. **Fig. 2b.** Directional deformation of model 1. **Fig. 2c.** Directional deformation of model 2. **Fig. 2d.** Strain vs time graph of model 1. **Fig. 2e.** Stress vs time of model 1. **Fig. 2f.** Strain vs time of model 2. **Fig. 2g.** Stress vs time of model 2.



(a) (b)

Fig. 3. Analysis outcomes of finalised model using PETG and TPU. Fig. 3a. Strain vs time graph. Fig. 3b. Stress vs time graph

4 Experimental Investigation

The “finalised model (Fig. 1b.)” is slated for 3D printing, with considerations for utilizing TPU filaments, PLA filaments and PETG filaments contingent upon the test results. 3D printing will provide a physical prototype for further assessments and tangible demonstrations. The process of fabricating auxetic lattices involved the utilization of 3D printing technology, specifically employing polyflex filaments. Initially, a set of prototypes consisting of 3x3 unit cells was created in two proposed combinations of PLA, PETG and TPU filaments.

PLA's stiffness and ease of printing made it an excellent practical choice for forming the lattice framework. PETG was utilized as it provides a balance between flexibility and structural integrity. PETG's enhanced impact resistance and durability made it suitable for specific lattice components requiring resilience. Furthermore, TPU was incorporated into each lattice, with a significantly lower Young's modulus. TPU's exceptional elasticity and flexibility rendered it ideal for lattice elements demanding high deformability and energy absorption.

Each material's unique mechanical properties were strategically leveraged to impart desired characteristics to the auxetic lattice, such as negative Poisson's ratio behaviour and enhanced mechanical resilience. These materials were chosen for their flexibility and suitability for additive manufacturing processes. To create the metamaterial structures, a concrete mixture was prepared with a maximum water to cement ratio of 0.475. Careful attention was given to avoid excess water content, which could compromise the final properties of the concrete.

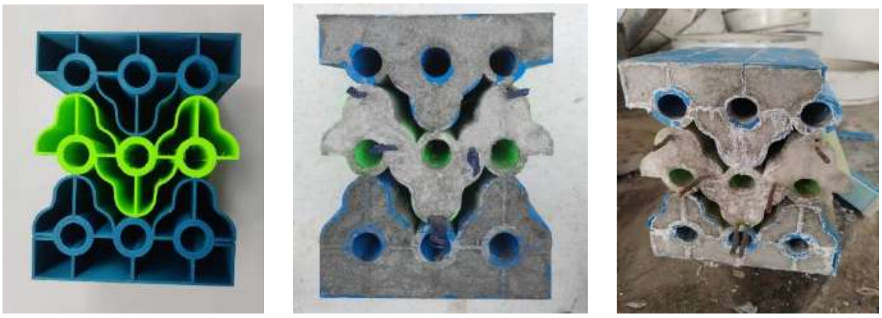


Fig. 4a. 3D printed prototype 1 of 3x3 unit cell Fig. 4b. Polymer lattice filled with self-sensing concrete Fig. 4c. Disintegrated PLA-TPU model

During the pouring process, meticulous care was taken to prevent any distortion of the polymer lattice geometry as distortion could negatively impact the compressibility and overall performance of the composite material. The consolidation step ensured proper compaction of the concrete mixture within the lattice structure. After adequate curing period, the blocks underwent compression tests and resistance measurement for self-sensing behaviour analysis.

The PLA – TPU model exhibited excessive chemical degradation. PLA is known for its biodegradability and, consequently, hydrolytic degradation happened when exposed to water over time. This poor water resistance caused the PLA to break down, the combination of substantial thermal expansion and chemical degradation resulted in a weakened bond between the concrete and the PLA in the composite compromising its structural integrity. Whereas, PETG – TPU model was structurally intact. The UTM facilitated real-time recording of the load-displacement data, and resistance values were captured simultaneously using multimeter and plotted against the applied load.

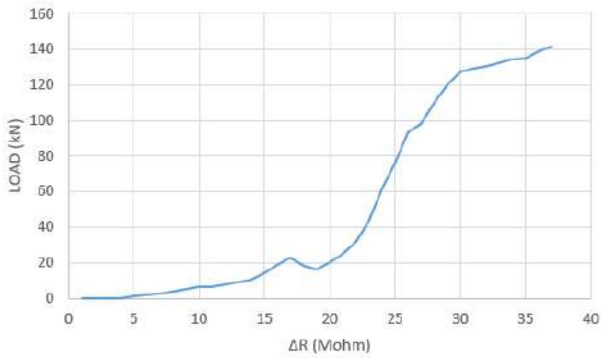


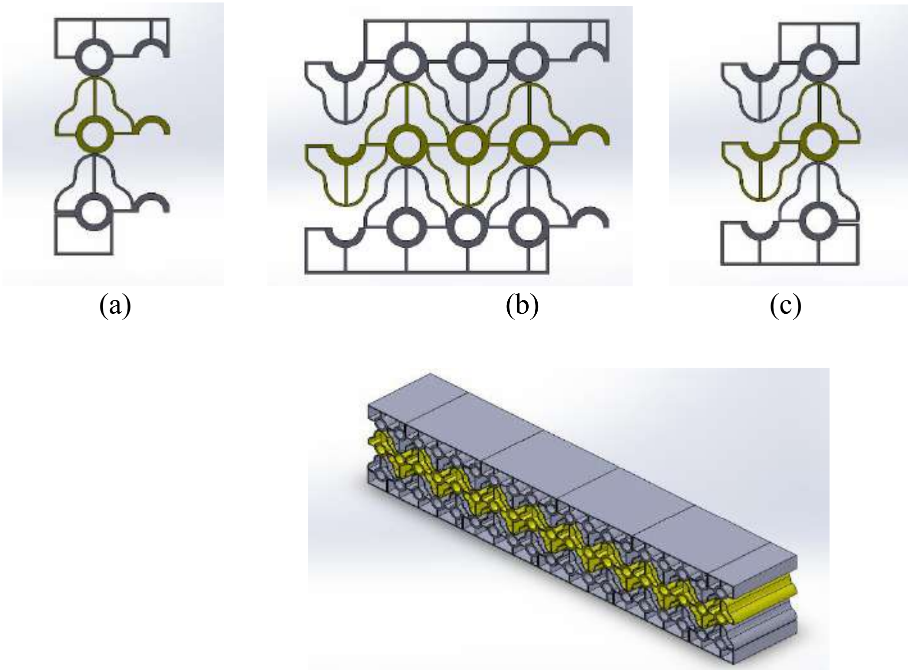
Fig. 5. Load vs resistance graph

Resistance measurement was done in 3 points of the model by connecting multimeters simultaneously during loading. All the points which were in tension region showed continuous response in resistance with load and resistance increased simultaneously from the point of initial crack, integrating the self-sensing behaviour. The self-sensing concrete within the PETG-TPU model effectively signals the progression of damage and the approach of failure, offering valuable real-time data for structural health monitoring. This combined analysis demonstrates the PETG-TPU composite's potential as a reliable and sensitive material for applications requiring both mechanical robustness and self-monitoring capabilities.

5 Future Scope

5.1 Development of Structural Member

To further explore the aspect of the metamaterial block as a structural member a beam was developed by keeping the selected metamaterial block as base module. An interlinking geometry facilitated for the development of the structural member. The beam was modelled in SolidWorks software.



(a) (b) (c)

(d)

Fig. 6. Beam model diagrams **Fig. 6a.** Beam left unit cell **Fig. 6b.** Beam centre unit cell **Fig. 6c.** Beam right unit cell **Fig. 6d.** Beam assembled model

5.2 Practical Applications

The proposed metamaterial self-sensing concrete system holds several practical applications which are yet to be researched on. This composite concrete can be used for the development of various smart infrastructure systems. This concrete system can be used in airport runways for reducing the runway length, in machine isolators, gym flooring and as efficient smart self-sensing building elements which aid in SHM.

6 Conclusion

In summary, the limitations of concrete such as brittleness and limited tensile strength, have spurred extensive research to enhance its long-term performance. Mechanical metamaterials, with engineered structures, showcase remarkable mechanical attributes. The analysis was conducted in different metamaterial models and different material combinations. Polymer lattices were modelled in SolidWorks software and analysed in ANSYS software.

The integrated metamaterial self-sensing concrete when analysed, exhibits high compressibility, mechanical tunability, and sensing capabilities, marking a groundbreaking advancement in lightweight concrete materials. The concrete's compressible property truly lies within the polymeric auxetic lattice geometry, making it more apt to recognize the overall design as a concrete reinforced polymer. Large scale testing can be done in future to validate the proposed model. More concentration can be given to analyse different material and unit cells to create different models. By delineating the boundaries and parameters, this research aims to contribute valuable insights to the existing knowledge base within the field of concrete technology. Additional investigation into different mechanical and SHM facets is necessitated by the innovativeness of the proposed idea.

REFERENCES

1. Karbhari, V.M., Ansari, F.: Structural health monitoring of civil infrastructure systems.UK: Woodhead Publishing Cambridge; (2009).
2. Asprone, D., Menna, C., Bos, F., Salet, T., Mata-Falcón, J., Kaufmann, W.: Rethinking reinforcement for digital fabrication with concrete. Cement and Concrete Research, vol. 112, pp. 111-121, (2018).
3. Wang, L., Ma, G., Liu, T., Buswell, R., Li, Z.: Interlayer reinforcement of 3D printed concrete by the in-process deposition of U-nails. Cement and Concrete Research, vol. 148, (2021).
4. Scerrato, D., Giorgio, I., Della, C., Madeo, A., Dowling, N.E., Darve, F. Towards the design of an enriched concrete with enhanced dissipation performances. Cement and Concrete Research, vol. 84, pp. 48-61, (2016).
5. Abedi, M., Fangueiro, R., Correia Antonio, G.: A review of intrinsic self-sensing cementitious composites and prospects for their application in transport infrastructures, Constr. Build. Mater. 310 (2021).
6. Monteiro, A.O., Loredo, A., Costa, P.M.F.J., Oeser, M., Cachim, P.B.: A pressure sensitive carbon black cement composite for traffic monitoring, Constr. Build. Mater. 154 1079–1086 (2017).
7. Ding, Y.N., Chen, Z.P., Han, Z.B., Zhang, Y.L., Pacheco-Torgal, F.: Nano-carbon black and carbon fiber as conductive materials for the diagnosing of the damage of concrete beam, Constr. Build. Mater. 43 233–241 (2013).
8. Wu, S.P., Mo, L.T., Shui, Z.H., Chen: Investigation of the conductivity of asphalt concrete containing conductive fillers, Carbon 43 (7) 1358–1363 (2005).
9. Chen, B., Wu, K., Yao, W.: Conductivity of carbon fiber reinforced cement-based composites, Cem. Concr. Compos. 26 (4) 291–327 (2004).
10. Naqi, A., Abbas, N., Zahra, N., Hussain, A., Shabbir, S.Q.: Effect of multi-walled carbon nanotubes (MWCNTs) on the strength development of cementitious materials, J. Mater. Res. Technol. 8 (1) 1203–1211 (2019).
11. Ding, Y.N., Liu, G.J., Hussain, A., Pacheco-Torgal, F., Zhang, Y.L.: Effect of steel fiber and carbon black on the self-sensing ability of concrete cracks under bending, Constr. Build. Mater. 207 (2019).
12. Konsta-Gdoutos, M.S., Aza, C.A.: Self-sensing carbon nanotube (CNT) and nanofiber (CNF) cementitious composites for real time damage assessment in smart structures, Cem. Concr. Compos. 53 162–219 (2014).
13. Barri, K., Jiao, P., Zhang, Q., Chen, J., Wang, Z. L., & Alavi, A. H.: Multifunctional meta-tribomaterial nanogenerators for energy harvesting and active sensing. Nano Energy, 86, 106074 (2021).