B. Tech Project Report

on

Estimation of carbon footprints for geosynthetic reinforced pavements using AI-ML

by

Alok Kumar (220004006)

Department of Civil Engineering

Indian Institute Of Technology Indore, Simrol,

Madhya Pradesh - 453552

Indian Institute of Technology Indore

Estimation of carbon footprints for geosynthetic reinforced pavements using AI-ML

A Project Report

Of

Bachelor of Technology

in

Civil Engineering

Submitted by

Alok Kumar (220004006)

Guide by:

Dr. Baadiga Ramu

DEPARTMENT OF CIVIL ENGINEERING
INDIAN INSTITUTE OF TECHNOLOGY INDORE

SIMROL, MADHYA PRADESH - 453552
September 2025

Acknowledgments

I would like to express my sincere gratitude to my project guide, **Dr. Baadiga Ramu**, for their invaluable guidance, support, and encouragement in this project. I would also like to thank DUGC Civil **Dr. Kaustav Bakshi** and HOD CE **Dr. Gourab Sil** for their constant support. Without their support, this report would not have been possible.

ALOK

Declaration

I hereby declare that the project entitled **"Estimation of carbon footprints for geosynthetic reinforced pavements using AI-ML"** work submitted for Mid-Semester Evaluation is completed under the supervision of **Dr. Baadiga Ramu, Assistant Professor, Civil Engineering IIT Indore**.

Alok Kumar

Alok Kumar,

23/09/2025

Certificate

This is to certify that the Mid-Semester Project Report entitled "**Estimation of carbon footprints for geosynthetic reinforced pavements using AI-ML**" is bonafide work of **Mr. Alok**. This work has been carried out by him under my guidance and supervision.

Baadiga Ramu

Dr. Baadiga Ramu,

23/09/2025

Preface

This report on "**Estimation of carbon footprints for geosynthetic reinforced pavements using AI-ML**" has been prepared under the guidance of **Dr. Baadiga Ramu** as a part of the academic requirement for Mid-Semester Evaluation. This project focuses the development of a robust regression-based framework to estimate total carbon emissions in pavement design. Using the LTPP dataset, multiple machine learning regression models were trained and evaluated to provide a reliable prediction tool for calculating emissions associated with pavement construction.

ALOK KUMAR

B.Tech. 4th YEAR

Roll No. 220004006

Department of Civil Engineering

IIT Indore

TABLE OF CONTENTS

1. Introduction
2. Objectives
    - 2.1. To Build a Dataset from Multiple Reliable Sources
    - 2.2. To Perform Exploratory Data Analysis (EDA) and Visualization
    - 2.3. To Estimate Carbon Footprint of Pavement Structures
    - 2.4. To Compare Asphalt Concrete (AC) and Portland Cement Concrete (PCC) Pavements
    - 2.5. To Develop an AI/ML-Based Prediction Model
    - 2.6. To Classify Pavement Designs Based on Emission Ranges
3. Literature Review
    - 3.1. Standards of Pavement Design in India
    - 3.2. Long-Term Pavement Performance (LTPP) Database
    - 3.3. Carbon Emission Factors for Pavement Materials
    - 3.4. Use of Machine Learning and Artificial Intelligence in Pavement Engineering
4. Methodology
    - 4.1. Overall Approach
    - 4.2. Data Collection
    - 4.3. Data Pre-Processing
    - 4.4. Calculation of Emission Values
    - 4.5. Machine Learning Model Development
    - 4.6. Development of user input/output system
5. Results and Discussion
    - 5.1. Dataset Overview
    - 5.2. Visualization of Pavement Dataset
    - 5.3. Regression Model Performance Comparison
    - 5.4. User Prediction System
    - 5.5. Discussion
6. Future Work
7. References

1. Introduction

Many people refer to roads as the foundation of a country's development. Better road infrastructure is becoming more necessary for a developing nation like India, which has the highest population in the world and one of the fastest growing economies. After the United States, India is the second country in the world which has largest road network, with over 6.6 million kilometers of roads[1].Villages to cities, industries to markets and people to opportunities are all connected by this large network of roads.

But, the rapid growth of road construction is putting serious pressure on the environment. The carbon footprint emission is one of the most serious issues related to construction work. The entire amount of greenhouse gas (GHG) emissions, mostly carbon dioxide (CO_2), that are released into the atmosphere as a result of human activity is known as the carbon footprint. There are several phases of road construction that contribute to carbon emissions:

- *Extraction and processing of raw materials* such as bitumen, aggregate, cement and steel.
- *Transportation of materials* from production plants to the construction site.
- *Energy consumption* in machinery and equipment used for mixing, paving, compaction, and curing during construction.
- *Maintenance and rehabilitation activities* carried out during the life cycle of the road.

According to research, almost 23% of global CO_2 emissions come from the construction sector alone, with pavement construction contributing significantly to the total CO_2 emission [8]. The new and modified construction plans of the government of India are resulting in the construction of thousands of kilometers of new highways, expressways and rural roads every year for development of the country. In addition to making strong and cost-effective pavements, it is crucial to make them environment friendly.

Pavement engineers gave priority to mainly three factors: cost-effectiveness, durability and structural strength. These are necessary, but they ignore the sustainability issue. Even if a pavement design may be less expensive for the short term, but its high carbon emissions may cause of climate damage far more for long term. As a result, sustainability has joined as the fourth factor of pavement design.

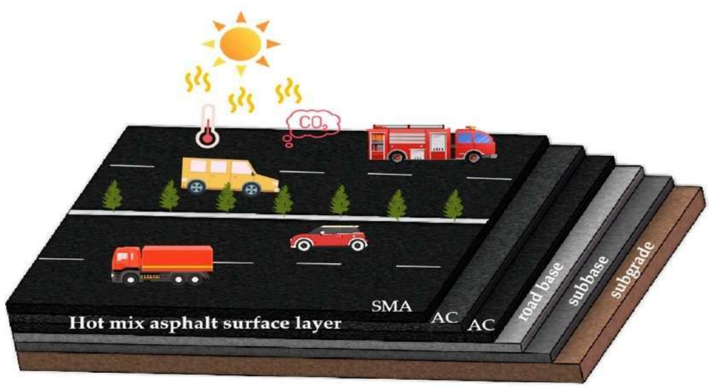

Fig 1. Pavement Structure of Asphalt Concrete *[11]*

To resolve this issue, engineers need reliable methods to quantify and compute carbon emissions from different pavement types. With the help of such estimates, designers and government officials can make proper decisions that will limit their impact on environment. For example, They might select a pavement type having a lower-carbon emissions, use thick layers when feasible or substitute low carbon materials like fly ash, recycled aggregates or geosynthetics for conventional ones.

Machine Learning and Artificial Intelligence provide a breakthrough opportunity in this regard. By analysis of large datasets of pavement designs and related emissions, machine learning techniques can identify trends and predict emissions for new pavement designs. Instead of continuously performing calculations manually, engineers can use AI models that offer quick, accurate and layer-by-layer breakdowns of emissions. In addition to saving time, this approach makes eco-friendly design decisions possible for real projects.

The project, titled **"***Estimation of Carbon Footprint for Geosynthetic Reinforced Pavements using AI/ML***"** is focused on addressing this challenge. Building a collection of pavement designs, calculating their emissions using established emission factors, and then training machine learning models to forecast emissions for any given pavement design are our objectives. Additionally, the research focuses on categorizing the emission results into "Highly Sustainable", "Sustainable", "Moderately Sustainable", "Unsustainable" and "Highly Unsustainable". This classification facilitates the interpretation of findings and the pursuit of environmentally friendly building by engineers and politicians.

This initiative is also highly relevant for academic and research as well. International research, especially from the US and Europe, has focused on pavement carbon emissions, despite the lack of studies in the Indian context. The decision-making process for the majority of pavement designs in India still does not incorporate carbon footprint assessments. Because of this, our work is not only novel but also desperately needed in the current environment.

2. Objectives

The current study addresses the larger problem of reducing climate change in addition to technical pavement design. As a result, we have both technical and sustainability-driven objectives.

Current work till now has been guided by the following primary objectives:

2.1 To Build a Dataset from Multiple Reliable Sources

The foundation of any AI/ML project is a solid dataset. Therefore, one of our goals is to gather, clean, and arrange data from multiple sources, including the Long-Term Pavement Performance (LTPP) dataset [7], the guidelines of the Indian Roads Congress (IRC)[3], [4] . Creating a representative dataset that is appropriate for Indian conditions and large enough to train models is the goal here.

2.2 To Perform Exploratory Data Analysis (EDA) and Visualization

Visual and statistical analysis of the dataset is another objective before beginning model training. Understanding distributions, trends and correlations between variables is made easier with the help of EDA. Examples:

1. Are PCC pavements always more polluting than AC pavements?
2. In terms of overall emissions, which layer is most responsible?

Visualizations such as bar charts, pie charts and comparative plots make the data easily understandable and explainable.

2.3 To Estimate Carbon Footprint of Pavement Structures

The main objective is to create a useful technique for estimating the carbon emissions related to pavement construction. There is the need of a thorough analysis of the materials used in each pavement layer, including the base, sub-base, subgrade and surface layers and their proportions also. It is necessary to use standardized emission factors because different materials have different emission factors. Example, cement has a much higher carbon intensity than aggregates.

To calculate the total carbon footprint for each type of pavement we have to establish a connection between pavement thickness and material emission factors.

2.4 To Compare Asphalt Concrete (AC) and Portland Cement Concrete (PCC) Pavements

Portland Cement Concrete pavements and Asphalt Concrete pavements are the two most common pavement types in India. Although each one has different structural benefits and economical factors. Their effects on the environment are also very different. The use of cement in PCC pavements results in higher carbon emissions during construction process, whereas bitumen in AC pavements causes higher emissions during maintenance period. Compare carbon emissions of AC and PCC pavements in order to determine which is more environment friendly in the Indian context is one of the main objective of our project. But the focus of this project is only on construction phase.

2.5 To Develop an AI/ML-Based Prediction Model

Predicting carbon emissions for any given pavement design using machine learning models is another key goal. Conventional approaches involve laborious computations and manual consultation of design codes such as IRC 37 [3]. By training ML models on large datasets, we aim to build a system where a user simply enters inputs such as:

1. Pavement type (AC or PCC)
2. Thickness of layers (base, subbase, subgrade, surface)

and the system provides a breakdown for every layer as well as an instantaneous prediction of the total emissions per lane per kilometer. This goal increases the process's scalability, speed, and practicality.

2.6 To Classify Pavement Designs Based on Emission Ranges

It is not enough to just make predictions; interpretation is just as crucial. To users, a figure like "2,80,000 kgCO_2e per lane-km" is hard to understand. So, we have tried to group the predicted total carbon emission values into five emission categories:

1. Highly Sustainable
2. Sustainable
3. Moderately Sustainable
4. Unsustainable
5. Highly Unsustainable

The results are actionable because of this classification. For example, users may attempt to use low-carbon materials or reduce the thickness of high-emission layers if a pavement design falls under "unsustainable". This classification will add a decision-support feature to our project.

3. Literature Review

A literature review is important for placing our study in the context of existing research and standards. The goal of our research is to integrate the disciplines of artificial intelligence, carbon emission studies and pavement design together or in a single framework because both have developed independently.

3.1 Standards of Pavement Design in India

Pavement design has traditionally focused on strength, durability, and cost-effectiveness. Codes of pavement design in India are primarily governed by the Indian Roads Congress (IRC).
IRC 37:2018: Guidelines for the Design of Flexible Pavements is the most pertinent document. This code offers techniques for figuring out asphalt (AC) pavement thickness based on variables such soil strength, traffic volume and weather [3].

For rigid pavements, *IRC 58:2015*: Guidelines for the Design of Plain Jointed Rigid Pavements for Highways. It provides specifications for Portland Cement Concrete (PCC) pavements including slab thickness, joint spacing and material requirements [4].

Note-: Although these codes offer structural and financial design solutions, they do not directly consider environmental factors like carbon emissions into account. Our initiative intends to close this gap by combining pavement design with carbon footprint analysis.

3.2 Long-Term Pavement Performance (LTPP) Database

One of the biggest open-access pavement databases in the world is the LTPP database, which was created by the Transportation Research Board (TRB) and the US Federal Highway Administration (FHWA) [7]. This contains data on:

1. Pavement structure and layer thickness
2. Traffic loading
3. Climatic conditions
4. Material types
5. Pavement performance over time

For our project, the pavement layer tables in the LTPP datasets have been particularly useful. These tables provide detailed information about the thickness of layers of pavements like base, subbase, subgrade, and surface layers, which we have used as the starting and main point for calculating carbon emissions [7].

3.3 Carbon Emission Factors for Pavement Materials

The average emissions per unit of material consumed are expressed as emission factors. There are several databases available:

1. Indian Life Cycle Inventory (ILCI) Database: Provides India-specific emission factors for major construction materials [10].
2. BIS Standards & Research Reports: Some IS codes and associated research also provide embodied energy/emission values [5].

Examples of typical emission factors ($kgCO_2e$ per cubic meter of material) include:

Pavement Layers	Assumed Emission Factor ($kgCO_2e/m^3$)
Cement Concrete (PCC)	320-350
Asphalt (Bituminous Layer)	200-250
Granular Subbase	40-60
Natural Aggregate	15-20

Table 1. Emission Factor of different Pavement Layers

Asterisk* *These values are not yet finalized and are used as a foundational dataset for model training. They only serve as a simplified method of illustrating the model's operation.*

3.4 Use of Machine Learning and Artificial Intelligence in Pavement Engineering

In recent years, AI and ML have increasingly been used in pavement engineering for:

1. Traffic and load prediction
2. Life Cycle Cost Analysis (LCCA)
3. Pavement performance modeling

However, few studies have predicted carbon emissions from pavements using machine learning. Spreadsheets and manual computations are used in the majority of emission studies. In order to present a new use of machine learning in sustainable pavement design, this project will train models (such as mlp, random forests, decision trees, and linear regression) using extensive datasets of pavement thickness and emission parameters.

4. Methodology

This project's methodology followed machine learning tools, environmental evaluation and engineering concepts. There are several stages to the procedure, which are described here.

4.1 Overall Approach

The aim of the project is estimation of the carbon footprint of pavement construction using actual pavement thickness data and material emission factors. The approach involves:

1. Collecting pavement layer data from LTPP database [7].
2. Take reference of Indian pavement design standards (IRC 37 and IRC 58) [3], [4].
3. Assigning emission factors for each pavement layers which is based on the composition and material type. (* Currently estimated values were used here)
4. Creating formula for emission estimation per lane-km.
5. Training machine learning regression models to predict emissions based on pavement type and layer thickness.
6. Allowing user input to simulate different pavement designs and compare emissions.

4.2 Data Collection

The main source of the data was the Long-Term Pavement Performance (LTPP) database, a worldwide standard reference for pavement related research [7]. It contains thousands of records of pavement sections with details such as:

1. Pavement family (Asphalt Concrete, Portland Cement Concrete)
2. Layer structure (surface, base, subbase, subgrade thickness)
3. Material type used in each layer

The pavement layer thickness and material properties data were the most important for our research and project. A structured dataset was created by extracting and pre-processing them.

4.3 Data Pre-Processing

There were several sheets and entries with inconsistent or missing values in the raw LTPP dataset. In order to prepare it for machine learning, the following pre-processing procedures were applied:

1. Filtering useful columns: Only pavement family, layer type and layer thickness were kept.
2. Handling missing values: Sections with missing thickness data were either imputed using median values for numerical columns and mode values for categorical columns.
3. Unit conversion: All thickness values given in dataset given in inches were converted to meters (m) for standardization.
4. Encoding categorical variables: Pavement type (AC, PCC) was converted into binary values (e.g., AC = 1, PCC = 0) which is important for regression model training.
5. Synthetic data generation: A normal distribution around mean thickness values was used to create synthetic entries when the dataset was too sparse for certain pavement combinations.

Pavement Type	Main layer	Thickness (m)	Emission Factor ($kgCO_2e/m^3$)	Layer Emission ($kgCO_2e$/ lane-km)
AC	Subgrade	2.1336	15	112014.0
AC	Subbase	0.20066	55	38627.05
AC	Base	0.18796	140	92100.401
AC	Surface	0.15748	200	112014.011
PCC	Subgrade	2.1336	15	112014.0
PCC	Subbase	0.1524	55	29337.0
PCC	Base	0.1524	200	106680.0
PCC	Surface	0.2616	320	293014.405

Table 2. Snapshot of pre-processed dataset. (*_Used assumed values of emission factor for model training purpose_)

4.4 Calculation of Emission Values

Each pavement layer (surface, base, subbase, subgrade) contributes differently to carbon emissions depending on material type.
**The emission factors used in this project were assumed solely for model training purposes*

1. Cement concrete (PCC surface layers): ~320–350 $kgCO_2e/m^3$
2. Bituminous asphalt (AC surface layers): ~200–250 $kgCO_2e/m^3$
3. Granular subbase/base (GSB/WMM): ~40–60 $kgCO_2e/m^3$
4. Aggregates: ~15–20 $kgCO_2e/m^3$

Step 1. Calculation of Layer Volume

The volume of each pavement layer was calculated using:

Layer Volume = Thickness (m)×Lane Width (m)×Length (1000 m for 1 km)

(A standard lane width of 3.5 m was considered for the project highway [6]).

Step 2. Calculation of Carbon Emission from Each Layer

The carbon emission for each layer was obtained as:

Layer Emission = Layer Volume × Emission Factor of the respective layer

Step 3. Total Carbon Emission per Lane-Kilometer

The overall emissions per lane-kilometer were calculated by summing the emissions from all pavement layers:

Total Emission = $\sum$ Layer Emission

4.5 Machine Learning Model Development

After preparing the dataset, machine learning models were trained to automatically predict carbon emissions. The process was as follows:

4.5.1 Input features

Pavement type (AC/PCC), layer thicknesses (surface, base, subbase, subgrade) and encoded the categorical columns in binary format.

Thickness (m)	Pavement type AC	Pavement type PCC	Main Layer Base	Main Layer Sub-base	Main Layer Subgrade	Main Layer Surface
0.09906	True	False	False	True	False	False
0.00000	True	False	False	False	False	True
0.05588	True	False	False	False	False	True
2.13360	False	True	False	False	True	False
2.13360	True	False	False	False	True	False

Table 3. Snapshot of encoded dataset used as input for model training

4.5.2 output variable

Total carbon emissions per lane-km ($kgCO_2e$) of each layer of pavement

Layer Emission ($kgco_2e$/lane-km)
19069.050466
0.000000
39116.000848
112014.000000
112014.000000

Table 4. Snapshot of output dataset for model training

4.5.3 Regression Model Tested

1. Ridge Regression
2. Lasso Regression
3. Linear Regression
4. Decision Tree Regression
5. XG Boost Regression
6. Support Vector Regression (SVR)
7. Random Forest Regression
8. Multi-Layer Perceptron (MLP)

4.6 Development of user input/output system

To make the model interactive and practical for users:

Users can enter:

- Pavement type (AC or PCC)
- Thickness of base, subbase, subgrade, and surface layers (m)

The model outputs:

- Predicted total carbon emission per lane-km
- Breakdown by layer (surface, base, subbase, subgrade)
- Comparison with emission categories ("Highly Sustainable", "Sustainable", "Moderately Sustainable", "Unsustainable" and "Highly Unsustainable") based on government benchmarks.

This feature makes users to modify thickness or materials to make construction more sustainable and helps them understand how design decisions affect emissions.

5. Results and Discussion

Pavement data was analyzed, emissions were estimated, and prediction models were trained using the process outlined in the previous section. This part summarizes the findings thus far and then discusses their importance.

5.1 Dataset Overview

After pre-processing the raw LTPP dataset, a structured dataset was prepared for model training. The dataset included:

- **Number of records**: More than 200,000 entries (after filtering)
- **Features considered**:
  - ➢ Pavement type (AC or PCC)
  - ➢ Layer thicknesses (surface, base, subbase, subgrade)
- **Target variable**: Total carbon emission per lane-km (kgCo_2e)

Pavement Type	Main Layer	Thickness (m)	Layer Emission per lane-km
PCC	Subgrade	2.13360	112014.000000
AC	Surface	0.03556	24891.999576
AC	Surface	0.02794	19558.000424
AC	Surface	0.16002	112014.003391
PCC	Subbase	0.40640	78232.000000
AC	Subbase	0.18542	35693.350933
AC	Surface	0.00508	3556.000053
PCC	Subgrade	2.13360	112014.000000

Table 5: snapshot of the filtered dataset

5.2 Visualization of Pavement Dataset

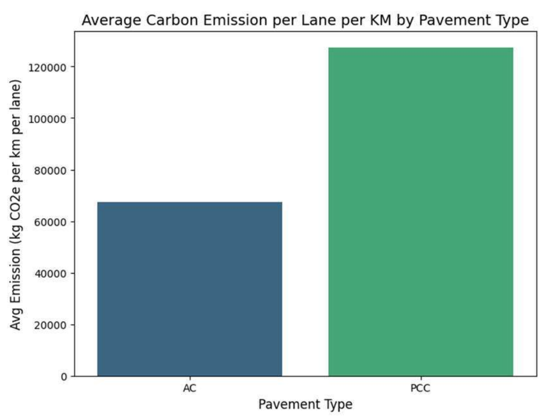

Fig 2. Average carbon emission for AC vs PCC

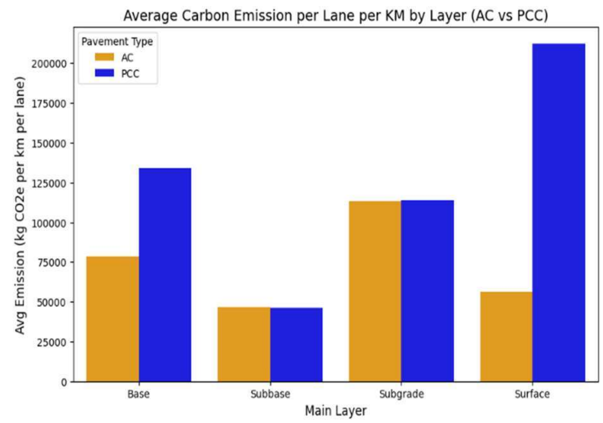

Fig 3. Base, Subbase, Subgrade, and Surface layer's respective average emissions contributions for both types of pavements (AC vs PCC)

5.3 Regression Model Performance Comparison

Model	R2	RMSE ($kgCO_2e$)	MAE ($kgCO_2e$)
MLP	1.0000	49.74	22.43
Random Forest	0.9999	219.47	4.6
Decision Tree	0.9998	878.86	297.94
XG Boost	0.997	3977.25	625.46
SVR	0.549	48916.92	22221.23
Linear Regression	0.492	51915.44	32898.87
Lasso	0.492	51915.44	32898.87
Ridge	0.491	51915.9	32900.26

Table 6: Performance comparison of different ML regression models

• R_2 demonstrates that MLP, Random Forest, and Decision Tree account for nearly all variability in emission prediction.

• RMSE and MAE show that, when compared to other models, MLP and Random Forest have the lowest prediction errors, making them the most dependable models.

• The MLP regression model performs the best overall for this project, with Random Forest coming in second.

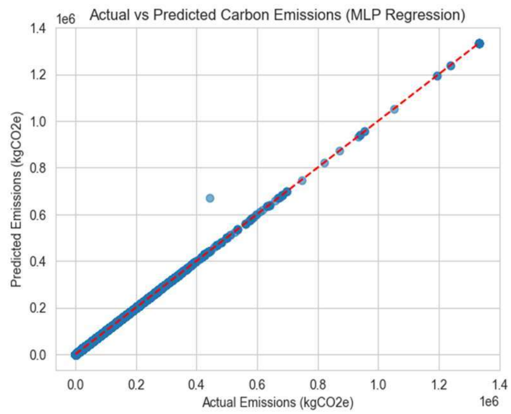

Fig 4. MLP Regression(Actual VS Predicted)

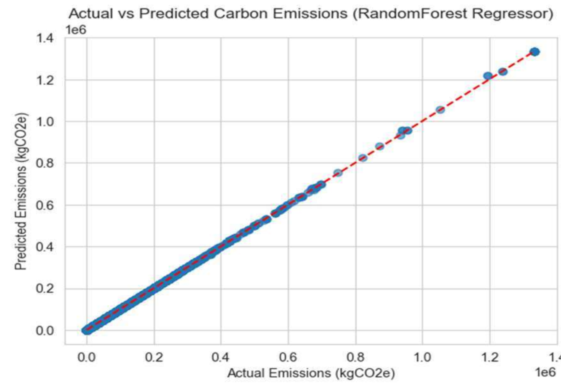

Fig 5. Random Forest Regression(Actual VS Predicted)

5.4 User Prediction System

The trained model was then integrated into a user input system, allowing users to provide total carbon footprints of the pavement. The system outputs:

- Predicted Total Carbon Emission ($kgCO_2e$/lane-km) for the pavement
- Layer-wise Breakdown of Carbon Emissions
- Categorization of Emissions (highly sustainable, sustainable, moderately sustainable, unsustainable, highly unsustainable) according to threshold values of carbon footprints

5.4.1 **Example and Validation**

We looked at an example situation where the user enters parameters for pavement type and layer thicknesses to show how well the created carbon emission forecast system performs. The total carbon emissions were then predicted using the trained Random Forest and MLP model, and the outcome was contrasted with the reference (calculated/original) values.

User input: Pavement Type – AC

Base Thickness: 0.15 m

Subbase Thickness: 0.33 m

Subgrade Thickness: 2.13 m

Surface Thickness: 0.05 m

output:

Layer	Predicted Emission (Random Forest) (kgCO2e)	Predicted Emission (MLP) (kgCO2e)	Original Emission (kgCO2e)
Surface	35,560.0	34,969.80	35,000
Base	73,431.40	73,530.47	73,500
Subbase	63,563.50	63,521.48	63,525
Subgrade	1,12,014.0	1,11,843.62	1,11,825
Total	2,84,568.90	2,83,865.37	2,83,850
Absolute Error	718.9	15.37	

Table 7: Prediction Error Summary

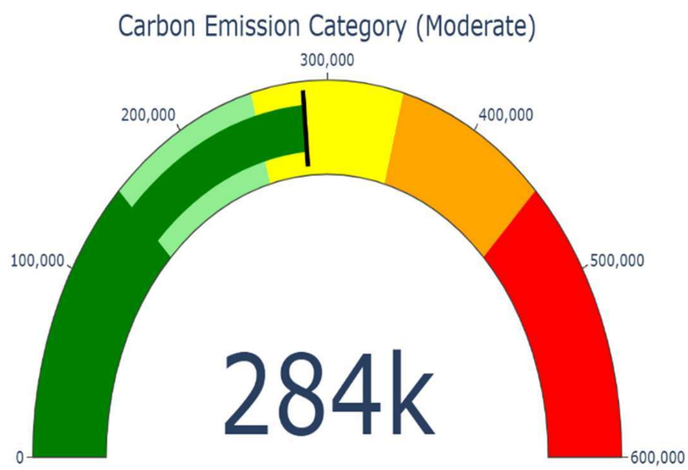

Fig 6. Gauge Chart of Output

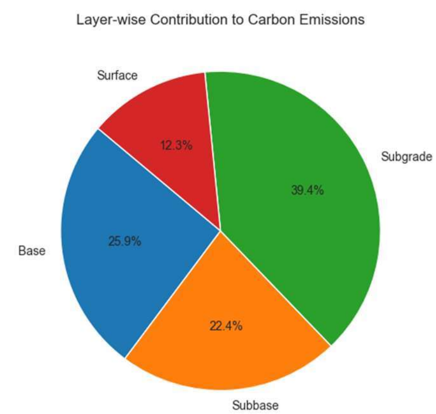

Fig 7. Percentage contribution of Layers

5.5 Discussion:

1. The findings clearly demonstrate that MLP and Random Forest is the best model for estimating carbon emissions.
2. Because thicker layers—particularly subgrade—dominate emissions, the layer-wise breakdown shows that using geosynthetics to reduce base/subbase thickness can greatly reduce emissions.
3. The categorization method gives users practical insights and provides the interpretation of outcomes.

6. Future Work

The construction of a machine learning-based pavement carbon emission prediction system is demonstrated in this study, although there are still a number of areas that need to be improved. Future research should focus on the following main areas:

1. Refinement of Emission Factors:

Emission factors for the base, subbase, subgrade, and surface pavement layers were either assumed or obtained from secondary sources for the current model.

This is a drawback since real emissions vary depending on the specific composition of materials used (e.g., percentage of cement, bitumen, recycled aggregates, moisture content).

Accurate emission factors will be calculated in future research using validated government datasets, Indian Standards (IRC Codes, Morth Guidelines) and using several research papers [2], [3], [6], [9].

2. Use of Advanced AI/ML Models

The ability of deep learning models, such as neural networks, to capture nonlinear interactions may be tested.

Robustness may be further enhanced by ensemble approaches that combine several regression models and algorithms.

3. Development Of User-Friendly Dashboard:

Streamlit or Flask can be used to construct an intuitive dashboard or web application that allows users to enter design parameters and receive emission projections with visuals instantaneously.

This can serve as a practical decision-support tool for users.

7. References

[1] *"Annual Report 2022-23, Ministry of Road Transport and Highways" (PDF). morth.nic.in. Ministry of Road Transport and Highways, Government of India. 31 December 2022. Archived (PDF) from the original on 18 September 2023. Retrieved 28 July 2023.*

[2] Indian Roads Congress (IRC). (2018). IRC 37: Guidelines for the Design of Flexible Pavements. New Delhi: Indian Roads Congress.

[3] Indian Roads Congress (IRC). (2014). IRC 58: Guidelines for the Design of Plain Jointed Rigid Pavements for Highways. New Delhi: Indian Roads Congress.

[4] Ambikesh Singh et al. / J. Environ. Nanotechnol., Vol. 12(4), 22-34 (2023). Carbon Footprint Estimation of Highway Construction Materials https://doi.org/10.13074/jent.2023.12.234480

[5]IRC:SP:84-2014 https://morth.gov.in/sites/default/files/Manual_for_Specifications_and_Standards_for_Four_Laning_of_National_Highways_through_Public_Private.pdf

[6] Laboratory and Field Studies on Geogrid-Reinforced Pavements: Performance Evaluation and Carbon Footprint Analysis https://doi.org/10.1007/s40098-025-01291-7

[7] Federal Highway Administration (FHWA). (2021). *Long-Term Pavement Performance (LTPP) Database*. Office of Infrastructure Research and Development, Washington, DC. Available at: https://infopave.fhwa.dot.gov

[8] International Energy Agency (IEA). (2020). *Tracking Industry 2020 – Cement.* Paris: IEA. https://www.iea.org/reports/cement

[9] Huang, Y., Bird, R., & Heidrich, O. (2009). Development of a life cycle assessment tool for construction and maintenance of asphalt pavements. Journal of Cleaner Production, 17(2), 283–296. https://doi.org/10.1016/j.jclepro.2008.06.005

[10] Garg, A., Shukla, P. R., & Bhattacharya, S. (2014). Indian Life Cycle Inventory Database (ILCID): Development of LCI database for Indian construction materials and energy sectors. The Energy and Resources Institute (TERI), New Delhi. https://www.teriin.org/projects/ilcid

[11] Liu, Y., Liu, Z., Zhu, Y., & Zhang, H. (2024). A Review of Sustainability in Hot Asphalt Production: Greenhouse Gas Emissions and Energy Consumption. Applied Sciences, 14(22), 10246. https://doi.org/10.3390/app142210246