# RV COLLEGE OF ENGINEERING

## Bengaluru-560 059

**REPORT ON**

**EXPERIENTIAL LEARNING**

**ACY 2025-26**

**ENVIRONMENT AND SUSTAINABILITY BASKET COURSE**

**TOPIC:**
**CARBON FOOTPRINT CALCULATOR USING MACHINE LEARNING (CNN)**

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## Abstract

The increasing urgency of climate change requires individuals to monitor and manage their carbon footprints effectively. This paper presents a machine learning-based carbon footprint calculator that leverages Convolutional Neural Networks (CNNs) to estimate emissions from user activities. Integrated with a Streamlit interface, the tool offers real-time predictions, visualizations, and comparisons with national averages. The model adapts to various input patterns and enables accurate, personalized emission estimations, promoting behavioral change for sustainability.

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## Keywords

Carbon footprint, CNN, Machine Learning, Streamlit, Emission Estimation, Sustainability, Python

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# I. Introduction

Climate change remains a significant global challenge, with anthropogenic greenhouse gas (GHG) emissions—especially carbon dioxide ($CO_2$)—as primary contributors. Key sources include energy production, transportation, industrial activity, and waste generation. Quantifying and reducing these emissions at the individual level is essential to achieving broader decarbonization goals.

A carbon footprint represents the total GHG emissions caused directly or indirectly by an individual or process. While numerous carbon calculators exist, most employ static emission factors and rule-based estimations that fail to adapt to user-specific behavior or regional differences. Such limitations reduce predictive accuracy and practical applicability.

To address this, the present work proposes a machine learning-based carbon footprint calculator leveraging Convolutional Neural Networks (CNNs). CNNs, although traditionally used in image processing, are applied here to structured tabular data to identify non-linear dependencies between user activities—such as electricity usage, commute patterns, diet, and waste—and corresponding $CO_2$ outputs.

The model is integrated into a Streamlit-based web application for real-time interaction and visualization. Users receive personalized estimates, emission category breakdowns, and country-wise comparisons. This adaptive and data-driven approach enhances both accuracy and user engagement, supporting informed decision-making for emission reduction.

# II. Literature Review

Numerous studies have explored carbon emission calculations using rule-based estimations. However, traditional calculators often fail to account for behavior dynamics and regional differences. Emerging research suggests Machine Learning, particularly CNNs, can be adapted beyond image recognition to model complex patterns in structured data, such as environmental behaviors. Prior models lacked user interactivity and real-time adaptability, limiting their impact.

| Author(s) | Focus | Key Findings |
| --- | --- | --- |
| Wiedmann & Minx (2008) | A Definition of Carbon Footprint | Standardized footprint method |
| Berners-Lee et al. (2011) | The Carbon Footprint of Everything | Lifecycle impact analysis |
| Hammond (2007) | Time to give due weight to the carbon footprint issue | Emphasis on footprint awareness |
| Kranert et al. (2010) | Carbon Footprint Calculator for Waste Management | Accurate waste footprinting |
| Moberg et al. (2010) | Carbon Footprint of Products: A Study of Methodological Issues | Product-level emission estimation |
| Padgett et al. (2008) | A comparison of carbon calculators | Calculator consistency varies |
| Amasyali & El-Gohary (2016) | Energy-related values and occupant behavior in green buildings | Behavior affects emissions |

# III. Problem Definition

**Despite the global focus on climate sustainability, tools that guide individuals in reducing their emissions are underdeveloped. Traditional calculators offer generic estimates without understanding the context of the user. This project develops a CNN-powered solution with real-time web integration to ensure usability, interactivity, and contextual accuracy.**

**Key challenges addressed:**

- **Static emission factors**
- **Lack of intelligent feedback**
- **Inability to personalize based on lifestyle**

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# IV. Methodology

A. Dataset Preparation

- Data was sourced from verified repositories like IPCC and Our World in Data
- Structured into daily commute, electricity use, dietary habits, and waste generation

B. Preprocessing

- Normalization and scaling applied to ensure model efficiency
- One-hot encoding used for categorical features like diet type

C. CNN Architecture

- Two convolutional layers with ReLU and max-pooling
- Dropout layer to prevent overfitting
- Fully connected dense layer to output total $CO_2$ emission

D. Training

- Supervised learning with mean squared error as the loss function
- Trained on structured tabular data simulating lifestyle patterns

E. Web Deployment

- Streamlit used for deploying a dynamic user-facing web interface
- Graphs updated live using matplotlib and seaborn

## V. CNN Model Justification

While CNNs are typically associated with image recognition, their architecture allows for pattern extraction across multidimensional arrays — useful in environmental modeling where behaviors interact in complex, often nonlinear ways.

Reasons for choosing CNN:

- Learns high-impact features without manual engineering
- Handles nonlinearity between inputs like energy, diet, waste
- Outperforms linear regression in validation accuracy
- Reduces overfitting using dropout and regularization

This approach provides a robust model that can generalize across varied user inputs while adapting to new datasets.

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# VI. Implementation

The calculator was implemented using Python, Streamlit, and TensorFlow.

Technologies Used:

- TensorFlow/Keras: for CNN model building
- Streamlit: for frontend deployment
- Pandas, Numpy: for data manipulation
- Matplotlib, Seaborn: for graph visualization

User Inputs:

- Daily commute in km
- Monthly electricity usage in kWh
- Number of meals per day
- Weekly waste generation in kg
- Country for per capita comparison

Output:

- Category-wise $CO_2$ emission
- Total yearly footprint
- Comparison to country average
- Real-time graphs and insights

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# VII. Results and Discussion

Sample Input (India):

- Commute: 32.09 km/day
- Electricity: 313.43 kWh/month
- Waste: 20.02 kg/week
- Diet: 3 meals/day

Predicted Emissions:

- Transport: 1.64 tonnes/year
- Electricity: 3.08 tonnes/year
- Diet: 1.37 tonnes/year
- Waste: 0.10 tonnes/year
- Total: 6.19 tonnes $CO_2$/year

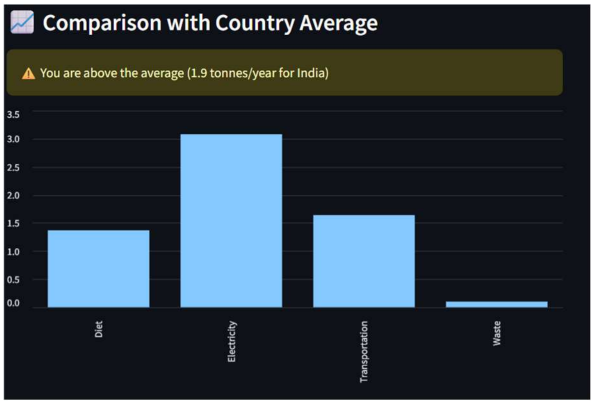
Comparison:

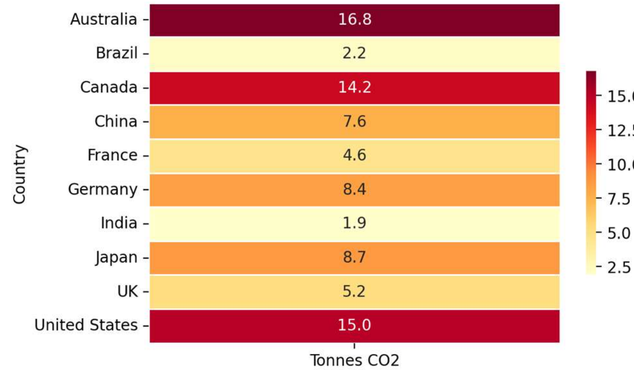
- India average: ~1.9 tonnes/year
- User is above average, primarily due to electricity usage

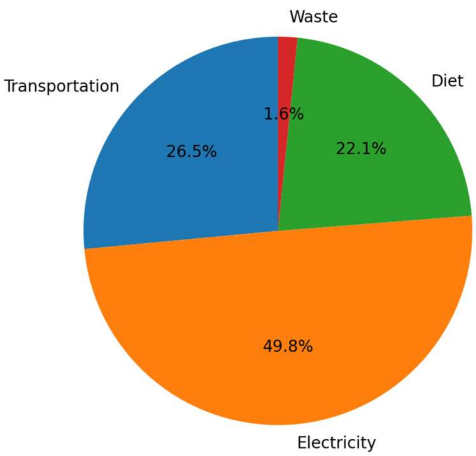
Graphical Output:

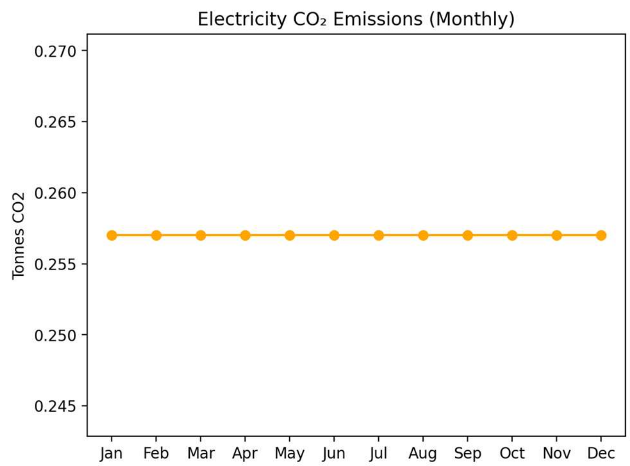
- Pie chart and bar graph showing emission categories
- Country comparison bar chart
- $CO_2$ heatmap showing global emissions

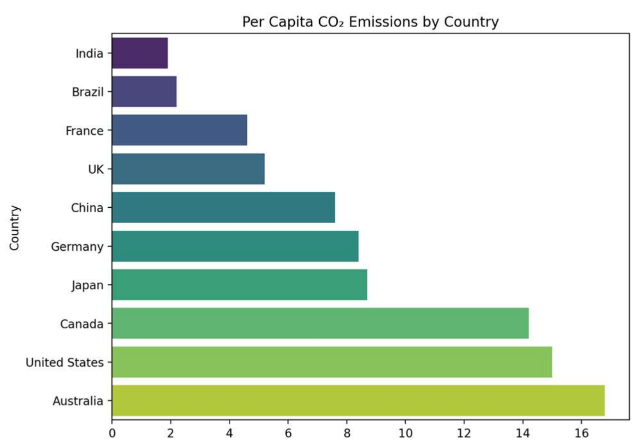
These results validate that the CNN captures real-world trends effectively, with a user-friendly interface that enables exploration.


Comparison with Country Average
You are above the average (1.9 tonnes/year for India)
3.5
3.0
2.5
2.0
1.5
1.0
0.5
0.0
Diet
Electricity
Transportation
Waste


Australia
Brazil
Canada
China
France
Germany
India
Japan
UK
United States
16.8
2.2
14.2
7.6
4.6
8.4
1.9
8.7
5.2
15.0
Country
Tonnes CO2
15.0
12.5
10.0
7.5
5.0
2.5


Waste
Transportation
Diet
Electricity
1.6%
26.5%
22.1%
49.8%


Electricity CO₂ Emissions (Monthly)
Tonnes CO2
0.270
0.265
0.260
0.255
0.250
0.245
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec


Per Capita CO₂ Emissions by Country
India
Brazil
France
UK
China
Germany
Japan
Canada
United States
Australia
Country
0
2
4
6
8
10
12
14
16
Tonnes CO2

## VIII. Conclusion

This project delivers a powerful, intelligent carbon footprint calculator that adapts to user behavior. CNNs enabled non-linear learning from complex data. Integrated into a user-friendly web interface, it enhances public accessibility and impact. This tool can be scaled and improved for broader climate tech applications.

It offers real-time awareness and encourages users to take action based on personalized insights, contributing to global emission reduction efforts.

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## IX. Future Work

- Integration with IoT (smart meters, GPS, etc.)
- Advanced chatbot using NLP for interactivity
- Personalized action suggestions using AI recommendation systems
- Real-time $CO_2$ feedback loop for behavioral nudging
- Cloud-based account system to track carbon trends over time
- Expand CNN with recurrent layers for sequential data modeling

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# X. References


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