Journal of Engineering Science and Technology
Special Issue on AIEC2024 Vol. 20, No. 1 (2025) 118 - 132

AUTOMATED INFRASTRUCTURE SUSTAINABILITY ASSESSMENT: A DEEP LEARNING APPROACH FOR REAL-TIME CO_2 IMAGE ANALYSIS

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Abstract

This study investigates the potential of using deep learning for real-time image analysis in assessing sustainable infrastructure and urban development. Convolutional Neural Networks (CNNs) are implemented to evaluate live-captured building images, enabling automated classification and data extraction for decision-making. The proposed approach overcomes the limitations of existing methods by facilitating real-time analysis and large-scale data processing. A dataset exceeding 12,000 images rigorously evaluates the CNN model's performance. This research establishes a framework for leveraging deep learning for real-time assessment of sustainable infrastructure, paving the way for improved data-driven urban planning and development decision-making. The study confirms that the Inception Net V3-based feature extraction technique accurately classifies images based on CO_2 emission levels. This classification task is best performed using the Neural Network model. Advanced feature extraction techniques are essential for improved environmental image classification.

Keywords: Convolutional neural networks (CNNs), Data-driven decision-making, Deep learning, Real-time image analysis, Sustainable infrastructure, Urban development.

1. Introduction

The contribution of urbanisation and infrastructure development to global CO_2 emissions has been commonly recognised, motivating the search for urban planning practices with a smaller ecological footprint. Urban areas produce 70% + of carbon emissions, a key contributor to climate change. Given the global dynamics of rapid urbanisation and subsequent growth in the world's urban population, there is a growing urgency to seek solutions to monitor and mitigate the environmental impacts of urban infrastructure development [1]. Especially for a broader perspective of global sustainability targets as controlled by the United Nations, all-embracing CO_2 downgrading with real-time monitoring systems is unavoidable.

Current ways to understand if the infrastructure is sustainable or calculate everything that comes out of the stack and the balance of CO_2 emissions are being used more traditional methods that, on average, cost a lot, are laborious and can only present partial data live. Due to the demand for new efficient, scalable and real-time approaches in this field, more advanced environmental monitoring technologies like artificial intelligence (AI) and machine learning (ML) are being explored [2]. Deep learning AI, in particular, is revolutionising how CO_2 emissions are being monitored by providing automated processing of immense satellite imagery and sensor data volumes [3].

Convolutional Neural Networks (CNN), a class of deep learning models, have proven highly effective for image classification problems among multiple fields [4]. As seen in the example with this last comment, indeed, they have advanced a bit further: They are convolutional neural networks able to extract the relevant features from images and then classify the environmental data automatically, which gives great insight into the sustainability of infrastructure. While CNNs have vast potential, they offer several challenges related to selecting architectures, training models, and feature extraction techniques for accurate classification.

In this study, as AI intelligent tools, the approach of machine learning and deep learning have been dealt with to find a solution by deploying a real-time image classification system utilising CNNs to carry out CO_2 emission analysis. A state-of-the-art CNN, Inception Net V3, extracted features from the satellite images in a framework. These features are finally submitted to different machine learning models (Random Forest, Logistic Regression, Support Vector Machine (SVM), and Multi-Layer Perceptron (MLP)) to classify the images according to emission classes. This research aims to explore the capacities of these models in classifying levels of CO_2 emissions, and it can be considered as a basis for data-driven decision-making in initiatives related to urban sustainability.

In the methodology section, the dataset, the machine learning pipeline, and the models used in experiments, have been detailed. Results: Performance of models Discussion and Implications for Sustainable Infrastructure Assessment The conclusion concludes this research's main contributions and future work for improving real-time CO_2 emission monitoring systems.

2. On The Machine Learning Approach

Machine learning is a type of artificial intelligence that enables self-learning from data and then applies that learning without the need for human intervention.

2.1. A machine learning pipeline for image classification

Image Classification has transformed how we work with image data, thanks to machine learning. A well-defined machine learning pipeline provides systematic steps to convert raw images into actionable knowledge. The chain of events includes preprocessing, feature extraction, training test evaluation, and high-precision real-time classification of new images.

2.2. Image classification based on machine learning

In Earth Science, machine learning (ML) is a key to many applications, such as retrieval algorithms, sensor calibration or image classification tasks [5]. The main goal of ML in such an area is to automatically learn and extract valuable patterns or knowledge from data using various computational models emphasising pattern recognition and predictive/causal inference, which has been frequently referred to as the construction of ML model-related principles [6]. As a core part of AI, ML uses several algorithms that help models make data-driven decisions, essentially making computer programs improve their performance using a method very similar to how humans learn [7].

Machine learning (ML) represents a variety of techniques, such as supervised learning, unsupervised learning, semi-supervised and reinforcement learning, which differ in their underlying assumptions and practical applications [8]. ML systems can also learn incrementally by supporting human learning practices to iteratively improve their processes while reaching higher levels of cognitive capability [9]. In computer vision, assigning categorical labels to entire images, particularly specific segments, is an essential challenge. Automation of Image Structure and Labsophage Type Classification Automation of image structure detection, especially for image to isolate classification and lab ecotype extraction, simplifies the analysis workflow [10].

Convolutional Neural Networks (CNNs), competing with others among the algorithms employed, demonstrated state-of-the-art performance on multiple benchmark datasets [11]. A logistic regression algorithm also showed strong performance in classifying satellite cloud imagery and robust identification of cyclones [12]. The algorithm, Random Forest, has high predictive accuracy in all classes by categorising images using high-resolution infrared radiation [13]. Even if these techniques have obtained good results, the large amount of computational time they require makes it difficult to find cost-effective and practical ways to achieve high classification accuracy. This limitation requires continual work towards improving the speed of ML techniques to process and analyse expansive images.

2.3. Image classification based on deep learning

Image classification and feature extraction with deep learning have served very well. For example, the convolutional Neural Networks (CNNs) are a powerful model in deep learning [14] with a wide range of applications such as weather imaging, climate change assessment, smart grid optimization for sustainable supply chains and improving weather forecasting and disaster relief. Many researchers have evaluated this labelling model to decompose low-resolution images and extract the features of those images. Deep learning is commonly used in emotion recognition because of the precise classification and high accuracy rate in multi-classification tasks [15].

Many different CNN architectures, among which Google's Inception Net and ResNet, have been widespread across various image classification domains [16]. This owes to the depth of structure in these models, typically with deeper convolutional layers leading to more finely-grained output. Therefore, it is recommended that more current models like Inception V3 be used [17]. In [18], this model was used to classify forest fires in aerial images, achieving 88% accuracy.

There remains, however, a significant human/no-human scalability issue here for this technology and at least in the case where most of the time with architectures like VGG, Inception or ResNet (model) a considerable part of the spent amount of time training them, will go into labelling images that feed into it to train as well as checking manually on how Final accuracy is too short [19]. In addition, a single AI algorithm that can solve an image classification problem may have some limitations, so it requires optimisation with several other methods to address the complexity of the Image Classification task [20].

2.4. Image feature extraction using inception net

Inception Net by Google: Inception Net is a state-of-the-art deep learning framework mainly used for image recognition. The CCNet has been pre-trained on a large-scale annotated dataset containing more than fourteen million images, which is the ImageNet [21]. This framework has a structure with many parallel convolutional kernels and works along with one single max pooling layer. The outputs of each convolutional kernel are then passed to the next layer (after processing and adding them up). These kernels use nonlinear activation functions. These convolutional kernels are carefully positioned in a strategic way, which helps prevent overfitting through multiple layers and helps in making the network scalable, which will be of importance later on when our network gets deeper & prevent loss of information from earlier stages during the process of gradient descent.

Convolution kernels of varying sizes (1×1, 3×3, and 5×5) are used for convolution and pooling operations in the architecture of convolutional neural networks (CNNs) such as Inception Net. This network employs parallel processing, essential for extracting more complex feature maps [22]. This parallelism may bring consistently significant gains in the image classification task, as shown in Fig. 1 but it fails to be helpful for other tasks.

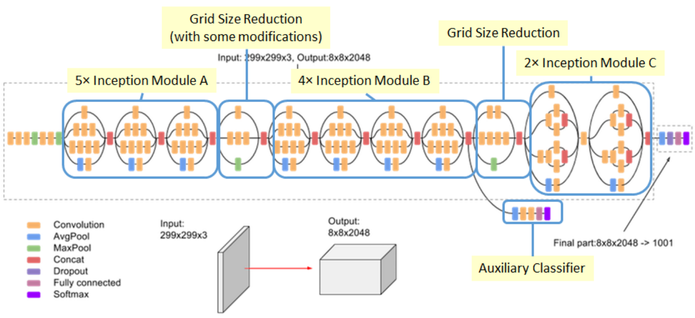

Fig. 1. Inception net. concept used in the current research.

2.5. Machine and deep learning algorithms

Satellite sensors provide an enormous amount of Earth observation data. This data is leveraged by Machine learning algorithms to automatically classify the satellite images. It enables scientists to distinguish characteristics such as land cover types or changes over time. This information is essential for environmental monitoring, urban planning and precision agriculture strategies.

2.5.1. Support vector machine.

SVMs are a supervised learning model which divides the attribute space into hyperplanes to allow an instance of a different class to maximise the distance between them and minimise structural risk. SVMs are designed to find an optimal separating hyperplane with a solid ability to generalise new data [23].

2.5.2. Logistic regression

A type of ML. It falls under the category of supervised learning. So, training on labelled data is required. LR is suitable for medium-scale problems and can also be used to solve regular binary classification or linear regression. It adopts a logistic function (Sigmoid) to model such data. This function ensures a value range of responses between 0 to 1, as shown in Fig. 2 [24].

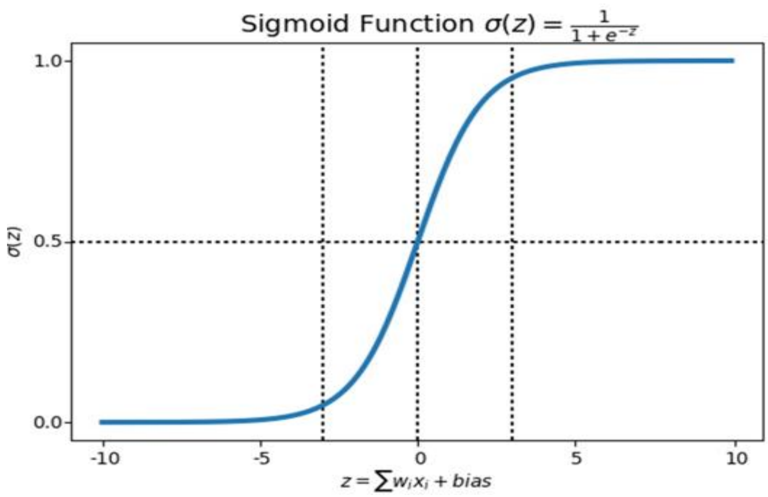

Fig. 2. Sigmoid function for logistic regression.

Usually, logistic regression uses maximum likelihood estimation (MLE) and a conditional probability as the loss function to evaluate the model. Assign class 0 if probability > 0.5 and vice-versa for predictions [25].

2.5.3. Random forest

One of the most common machine learning methods is a machine learning classification technique, which uses decision trees as its base. Its simple architecture and high performance are considered among the best languages. This method gives birth to two different types of random selection processes, and both are combined in this approach to reduce variance (and hence increase accuracy) and keep the bias low. The first approach, called bootstrap aggregation or bagging, is based on generating multiple training subsets by re-sampling with the replacement of the original dataset, followed by aggregating the predictions of those trained trees. The second method, random subspace selection, is another technique that chooses a subset of features randomly at a time and reduces the correlation among the trees to improve the model performance.

2.5.4. Multi-layer perceptron:

An algorithm which has been well-documented when dealing with broad-domain image classification for natural environments, Fig. 3. Various methods have been introduced to improve the performance of MLP, such as using weight initialisation schemes that perform well, working with combined spectral and spatial information for the classification of hyperspectral images, and employing state-of-the-art methods based on advanced architectures like MLP-Mixer for accurate hyperspectral image classification [26]. TL;DR: The single-layer Perceptron converged during training, but the same network with three layers of MLP was randomly initialised and did not converge right away, while a hybrid genetic algorithm with backpropagation technique optimised hyper-parameters for faster convergence of MLP during training classification or regression applications [27]. Classification results using different methods: The performance of MLP is promising, and we are also trying our best to improve it.

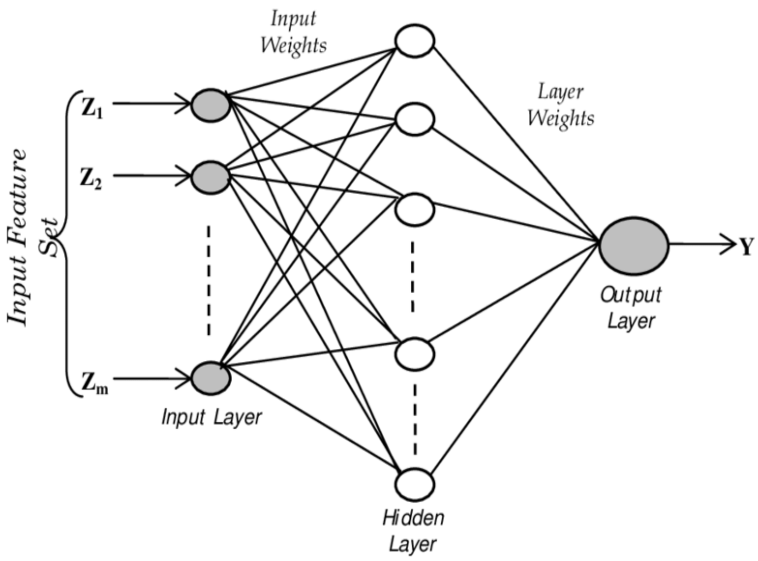

Fig. 3. Structure of multi-layer perceptron.

3. Methodology

3.1. Dataset description

The dataset used in this work was made available by Intel Corporation and is an image dataset from the vehicle tailpipe to categorise 25,000 labelled images into six categories of CO_2 emission levels. We consider categories of emissions levels that span "Extremely Low" to "Extremely High" with balanced class distributions, Table 1 and Fig. 4. These images are collected using satellite and used as input for evaluation by many machine learning and deep learning algorithms. The dataset is split into the following three sets: training (70%), validation set (15%), and test set (15%). This separation guarantees vital model training, regression and unprejudiced assessment of classification functionality [28].

Table 1. Distribution of image samples by emission categories.

Image class	Class Code	Image count	Percentage per class
Extremely low emissions	ELE	2271	16.18%
Very low emissions	VLE	2404	17.12%
Low emissions	LE	2274	16.20%
Medium emissions	ME	2512	17.89%
Very high emissions	VHE	2191	15.61%
Extremely high emissions	EHE	2382	16.97%
Total		14034	100%

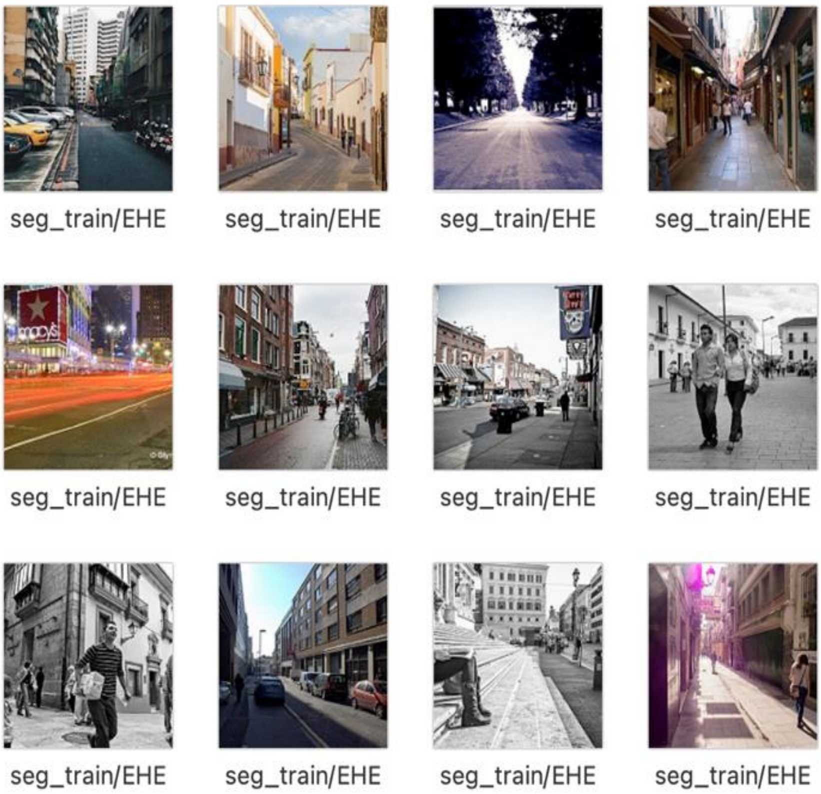

Fig. 4. Images of the extremely high-emissions class sample [28].

The aim is to classify images based on their CO_2 emission levels using feature extraction and machine learning models. The research methodology is summarised in Figs. 5 and 6.

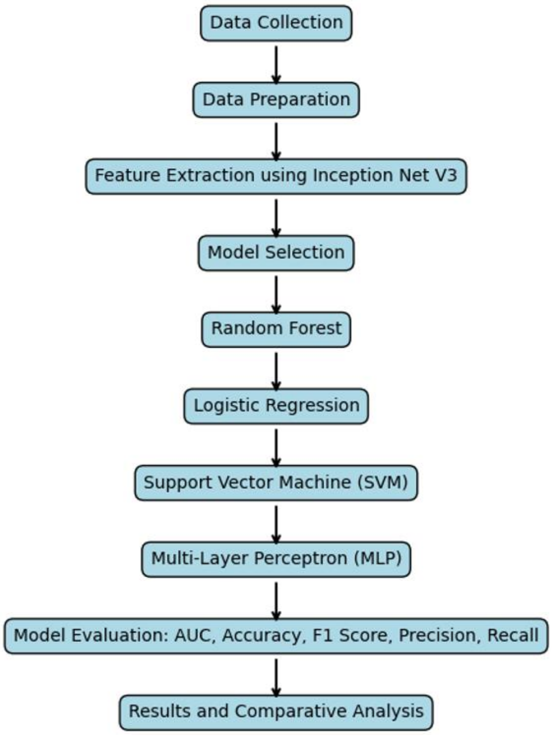

Fig. 5. The research methodology.

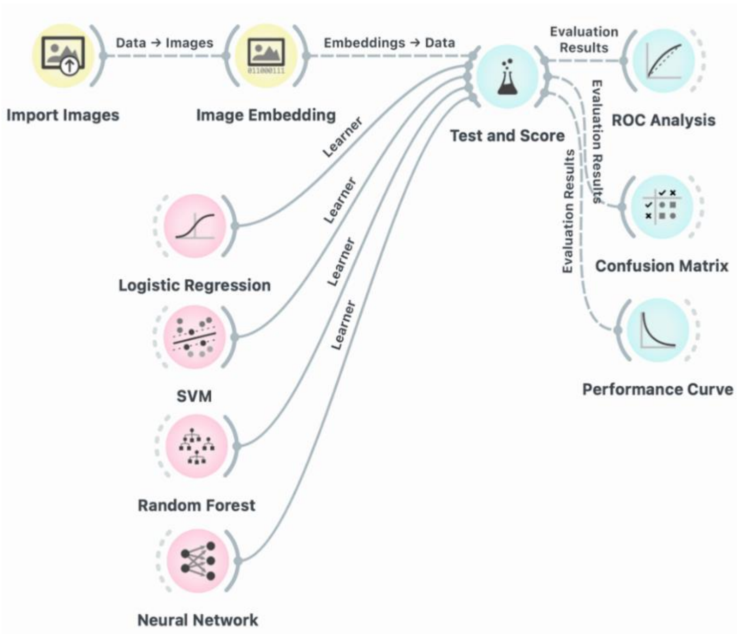

Fig. 6. Orange data mining workflow for classifying CO_2 emissions levels based on environmental images.

3.2. Machine learning pipeline

A well-structured machine learning pipeline was developed to perform the image classification task. This pipeline consists of several key stages:

3.2.1. Data preprocessing

The images in the dataset are first resized to a fixed dimension to standardise input for the models. Normalisation is applied to ensure consistent pixel values, improving model convergence.

3.2.2. Feature extraction

Google's Inception Net V3, a pre-trained convolutional neural network (CNN), is employed for feature extraction. This model was chosen due to its high performance in image classification tasks [29]. The Inception Net V3 architecture extracts high-level features from images, converting raw image data into structured feature vectors, which machine learning models can utilise. The network was pre-trained on the ImageNet dataset, containing over 14 million images, which helps recognise relevant patterns in environmental photos.

3.2.3. Model selection

Four machine learning models were selected for this study based on their established efficacy in classification tasks:

- Random Forest (RF): An ensemble learning method based on decision trees, known for its robustness in classification tasks.
- Logistic Regression (LR): This is a linear model widely used for binary classification, adapted here for multi-class classification.
- Support Vector Machine (SVM): A powerful algorithm for classification tasks, which finds the optimal hyperplane that maximally separates the classes.
- Multi-Layer Perceptron (MLP): A feedforward artificial neural network capable of learning complex patterns in the dataset.

3.3. Model training and evaluation.

Each of the four models was implemented and trained using the Orange Data Mining framework, which facilitates rapid prototyping of data analysis workflows. The pre-extracted features from Inception Net V3 were fed into each model. Hyperparameter optimisation was performed using a grid search to identify the best configurations for each model. The training was conducted on the training dataset (70% of the data), with model performance evaluated on the validation set (15%). After tuning, the final models were tested on the unseen test set (15%) to assess their generalisation ability.

3.4. Evaluation metrics

The performance of each model was evaluated using several key metrics:

- Area Under the Curve (AUC): Measures the ability of the model to differentiate between emission levels.

- Classification Accuracy (CA): Represents the percentage of correctly classified images.
- Precision and Recall: These metrics assess the model's ability to identify true positives and minimise false positives accurately.
- F1 Score: A harmonic mean of precision and recall used for evaluating models with imbalanced datasets.

3.5. Experimental setup

The machine learning and deep learning models were trained and evaluated on a high-performance computing environment equipped with GPUs for efficient model training. Inception Net V3 was implemented using the TensorFlow framework, while Orange was used to integrate the feature extraction and machine learning models into a cohesive workflow [30]. The results were analysed using Orange's built-in tools for model comparison, enabling an in-depth analysis of the classification performance across the four models.

4. Results and Discussion

4.1. Model performance

The classification performance of the four selected models-Random Forest (RF), Logistic Regression (LR), Support Vector Machine (SVM), and Multi-Layer Perceptron (MLP)-was evaluated using the test set. Table 2 summarises the performance of each model across key evaluation metrics, including AUC, Classification Accuracy (CA), F1 Score, Precision, and Recall (Table 2).

Table 2. Distribution of image samples by emission categories.

Model	AUC	CA	F1	Precision	Recall
Random Forest	0.985	0.886	0.885	0.885	0.886
Neural Network	0.993	0.920	0.920	0.920	0.920
Logistic regression	0.992	0.912	0.912	0.912	0.912
SVM	0.982	0.875	0.884	0.883	0.884

4.2. Performances on neural network

The detection was highest with the MLP Neural Network, 92%, and this model also obtained a score of 0.993 AUC value for the differentiation between CO_2 populations. This proves the effectiveness of predictions on emission level and the reliability, precision and recall were all fitted at 0.920 consistently. It is clear that the MLP model performs well off-the-shelf, and this can be due to its multilayered architecture, which allows it to learn very complex patterns in the high-dimensional feature space (extracted by Inception Net V3).

4.3. Logistic regression and random forest

This method with Logistic Regression gave a classification accuracy of 91.2% and AUC value =0.992. Despite being vastly simpler than the MLP, this model performed well thanks to Inception Net V3 doing a lot of the work in feature extraction. The model, Random Forest, performed very well in terms of accuracy, having an AUC close to 0.985 and an accuracy of 88.6%. It was the third previous logistic regression case. This further means that while Random Forest is good at capturing decision boundaries, its ensemble style might not be fully successful in mimicking the image data's complexity and high dimensionality.

4.4. Support vector machine

The SVM model also produced a higher AUC of 0.982 among the four models but exhibited lower classification accuracy (87.5%). This is especially the case with tuning SVM hyperparameters because not only does it have an additional level to tune for the non-linear kernel function, but this issue becomes even more complex in multi-class classification. When it came to Single Kernel SVMs for these larger data sets, they simply could not outperform the bigger models like the Neural Network that would have utilised these features extracted from an image much better.

4.5. Comparative analysis

Results The results clearly show that feature extraction using the inception Net V3 model gave 100% enhancement in the performances of all four machine learning models. The best overall system was the neural network due to its inherent ability to model non-linear relationships. Logistic Regression and Random Forest also did a good job (especially in AUC and precision), but they have such simple architecture that could not beat the more complex Neural Network.

4.6. Discussion

The performances of the Neural Network (MLP) and Logistic Regression models provide evidence that a proper feature extraction method is crucial for classifying CO_2 emission images. Experiments showed that using Inception Net V3 for feature extraction was efficient in converting the unprocessed raw satellite images to training-ready input data of classification models.

The marginally poorer performance of both the SVM and Random Forest models highlights a requirement for more optimisation, especially for hyper parameter tuning and selecting features. In the following, Ensemble methods or hybrid approaches that combine multiple models might be considered in potential work to boost classification accuracy further. Besides, even though the dataset used in this study was sufficient to serve as a preliminary classification database for CO_2 emission, future studies should extend data diversity by including images taken at different regions and variables atmospheric conditions. This would increase the generalisability of the models, thus widening their utility on deployment in real-world situations.

Moreover, real-time deployment of this deep learning framework on urban infrastructure monitoring could deliver valuable recommendations to municipal planners and decision-makers. Another possibility of its use is integrating it with the existing smart city infrastructure and building automated systems for ranking CO_2 that can assist real-time monitoring of environmental conditions so that informed decisions can be made in executing its sustainability effort.

4.7. Futu re directions

Although this study shows the potential use of deep learning in real-time CO_2 image reading, more studies are needed to further fine-tune our models for large-scale deployment. Further studies could address the inclusion of other data sources, including meteorological variables to enhance the model predictions in different settings for instance. In addition, the possible use of other CNN architectures like InceptionNetV4 and EfficientNet that are more advanced to have a more accurate classification were examined.

5. Conclusion

The study introduced an Inception Net V3-based deep learning framework for the real-time classification of CO_2 emission levels by satellite imagery with some feature extraction techniques. In this work, experimental results of machine learning models show that the Neural Network (MLP) and Logistic Regression have very high accuracy scores in classification, with 92% for the MLP model as the best performing one. These findings reinforce the utility of deep learning for environmental surveillance and suggest a scalable approach to evaluate sustainability in infrastructure while bolstering data-driven decision-making during urban development.

It also shows the type of premium that goes away with proper feature extraction on image classification tasks. The Inception Net V3 was able to capture high-level features from images, greatly enhancing the performance of all ML models tested in this study. It highlights the imperative to use more sophisticated architectures on complex environmental imagery.

But other lines of inquiry remain open. On the other hand, it was interesting to note that models like SVM and Random Forest, although quite strong, need more hyperparameter tuning and optimization to squeeze out as much juice from them. On the other hand, more environmental and even geographically diverse conditions could be tested to make it a global application.

In conclusion, this study demonstrates the potential of deep learning for automatic assessment of infrastructure sustainability, particularly helping city planners and policymakers become more aware to help reduce CO_2 emissions and support sustainable urban development. Additional data sources and the more robust CNN architectures that will be possible to test in the future have the potential to improve the accuracy and generalizability of this approach, providing a valuable resource for addressing important global environmental issues.

Abbreviations

CNN	Convolutional Neural Networks
ML	Machine Learning
MLE	Maximum Likelihood Estimation
MLP	Multi-Layer Perceptron
SVM	Support Vector Machine

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