engineering proceedings

MDPI

Proceeding Paper

Predictive Modeling of Biodegradable Material Degradation Using Deep Learning with An Improved Regulatory and Liability-Aware Approach †

Sanjay Bang *, Keya Purohit and Sreedhar Samarth

School of Law, CHRIST (Deemed to be University), Bengaluru 560029, Karnataka, India
* Correspondence: sanjay.satyanarayan@christuniversity.in
† Presented at the 4th International Electronic Conference on Processes, 20–22 October 2025; Available online: https://sciforum.net/event/ECP2025.

Abstract

There has been a significant rise in the adoption of biodegradable materials across industries. Industries including packaging, healthcare, and consumer goods need an accurate prediction of their degradation behavior to support environmental sustainability and ensure regulatory compliance. Here, we propose a deep learning-based framework that helps predict the decomposition rates and the associated environmental impact of biodegradable materials under diverse physicochemical conditions. We train the neural network on historical data of material performance, environmental exposure, and microbiological interaction, and the model shows its generalizability for life cycle estimation. The model has also been associated with an attention layer that monitors compliance with regulatory frameworks that govern material safety, quality, and consumer transparency. Standards and frameworks, including (ISO and ISI standards), are integrated into this layer to ensure adherence to product liability guidelines. Domain-specific regulations have been used to finetune the predictive outputs, keeping the permissible limits on product labeling, shelf life, and environmental claims. The approach shows better predictive results and demonstrates compliance with the legal context, and the model evaluation improves alignment with compliance thresholds and verification of the predictive results on the material life. Here, we explore a multidisciplinary approach that makes use of the learning abilities of ML algorithms and aligns the model performance with ethical frameworks to ensure trust and monitoring, creating intelligent systems for sustainable material design to improve sustainability and reusability, following regulations.

Keywords: biodegradable materials; deep learning; sustainability; regulatory compliance; attention networks; product liability

check for updates

Academic Editor: Adina Magdalena Musuc

Published: 13 April 2026

Citation: Bang, S.; Purohit, K.; Samarth, S. Predictive Modeling of Biodegradable Material Degradation Using Deep Learning with An Improved Regulatory and Liability-Aware Approach. *Eng. Proc.* **2025**, *117*, 73. https://doi.org/10.3390/engproc2025117073

Copyright: © 2026 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https://creativecommons.org/licenses/by/4.0/).

1. Introduction

The increasing industrial adoption of biodegradable materials has intensified research efforts toward understanding and predicting their degradation behavior under diverse environmental conditions. The environmental impact of these materials has increased the need for accurate degradation modeling. Technological advancements have led to fast and efficiently designed mechanisms that can enable us to determine these characteristics. Nowadays, much research is being done in designing not only deterministic modeling but also in predicting biodegradable material degradation. Emerging deep learning techniques provide powerful tools for modeling nonlinear degradation dynamics, especially in

materials design. Even though researchers have produced various solutions for the same issue, the integration of regulatory and liability contemplations is still a nascent area. The acceleration of screening and optimization of the biopolymer designing can be performed with deep learning models, but the complete regulatory and liability-aware method would require merging predictive models with explainable artificial intelligence (XAI). XAI is needed for transparency, assessing the risk towards indecision quantification, including the datasets involving regulatory compliance and life cycle assessment. Henceforth, precise research is required for developing the models that involve not only predicting degradation but also evaluating their impact on the environment as well as compliance with waste management regulations.

Nash et al. [1] have presented a clear summary of the applications of deep learning techniques in the areas of materials degradation. They have concluded that, by using deep learning techniques, the budget can be reduced along with increased safety and reliable detection. Ipek [2] has applied the convolutional neural networks for classifying the materials into biodegradable and non-biodegradable. They have shown the utilization of deep learning methods with a few pre-trained neural networks. A review on the assessment methods related to the degradation of the biomaterial by Hillary et al. [3] has highlighted employing cost-effective and efficient methods for the assessments. They have also given guidelines on the assessment parameters to be used for the same issue. The authors [4] have collected two datasets and have performed data balancing to have an equal number of biodegradable and non-biodegradable classes. They have utilized the support vector classification and achieved an accuracy ranging from 0.73 to 0.98. A complete study on biodegradable polymers, the suitable treatments, their composition, along with blending and modeling were performed by Samir et al. [5], which supports the researchers in understanding the recent advances of these polymers, which are biodegradable towards sustainable applications. The regulatory and compliance aspects have also been focused on by the authors in Refs. [6,7].

Zang et al. [8] have presented a predictive model for toxicity and proved that they can reduce the risk in the application process. Maksuda Khanam et al. [9] have provided a comprehensive analysis of the applications of machine learning models on the microplastics characteristics in the environment. They have given a detailed overview of the spectral methods as well as that of image-based methods with the integration of machine learning techniques. In Ref. [10], Xiaobo et al. have given a literature survey on the applications of machine learning models in the areas of life cycle assessment, which enables young researchers to have an idea of the existing techniques and their suitability for specific applications. In Ref. [11], the authors have formulated their prediction method with a sequence-to-sequence task creation with the support of natural language processing, along with a few reaction prediction processes. The authors have minimized the cost involved in human-generated rules. Here, the authors used a data-driven technique named enviFormer to predict biodegradation products and pathways without rules. They have utilized EnviroPath, which is a vast source of biodegradation reaction datasets. Transformer-based techniques and transfer learning are used by the authors for the training process. Prediction used the sequence-to-sequence translation mechanism. They have evaluated their proposed method and concluded that it can accurately predict the biodegradation reactions on more compounds in comparison with the existing techniques.

Sofia et al. proposed a machine learning-based framework [12] for predicting the working conditions and environmental actions of bio-based edible items wrapping materials with their contents, processing constraints, as well as environmental variables. Numerous machine learning algorithms, such as the Random Forest Technique, the Support Vector Regression Method, and Artificial Neural Networks, have been trained with the training

datasets taken from existing studies and lab-made datasets. The following parameters include the vital target variables involved, tensile strength, water vapor transmission rate, and the time taken for the biodegradation process. They found that the assembled models resulted in good prediction accuracy. Their research has highlighted the possibility of data-driven techniques for accelerating the progress of eco-friendly packaging resolutions having tailored properties, minimizing the trial-and-error investigation by encouraging circular economic ideas.

The article [13], titled "*An AI-Enabled Pathway for Biodegradability Prediction and Organic Material Discovery*", by Dela et al. presented a new technique for predicting the organic compounds' biodegradability. They have suggested an effortless way of representation named simplified molecular-input line-entry system (SMILES), as well as molecular images, which involves using AI-based prediction techniques, comprising convolutional neural networks and the long-short term memory (LSTM) methods, to extract meaningful features about the molecules along with their spatiotemporal relations. Reinforcement learning was incorporated for further enhancement of the model for better prediction, as well as finding new biodegradable materials. They have conducted the performance analysis of the proposed model and proved that the accuracy is nearly 87%.

Alhulaybi et al., in their research article [14], explored the polymer matrices' thermal decomposition, which is an enhanced biodegradable component that was made from a mix of Phoenix dactylifera L./high-density polyethylene (PD/HDPE) with the help of machine learning algorithms over the training dataset. The investigational results of the samples were attained through thermogravimetric (TGA) analytics below an oxidation-free environment, with heating rates of 10, 20, and 40 °C·min^{-1} and a degradation temperature ranging between 25 and 600 °C. The TGA analysis exposed the continual dependency of the real percentage weight loss of the materials by means of a test function comprising the degradation temperature, which shifts the thermograms into steady temperature maxima with growing heating rates. The cost function of the overall process was reduced with the help of deep neural network-based algorithms. Learning algorithms, together with optimized synaptic weights and biases, have been used for predicting the behavior of PD materials at temperatures from 600 to 1000 °C. This method predicted and optimized the PD and HDPE's thermal characteristics with better efficiency.

2. Methods

The current research used the following approach to study the predictive modeling of biodegradable material degradation using DL, emphasizing regulatory compliance and other liabilities. Figure 1 shows the methodology used for the study that integrates data-driven deep learning with regulatory compliance mechanisms to predict the degradation behavior of biodegradable materials. Data points used for the study include the data from material degradation experiments, environmental condition records, and regulatory standards. The captured data are then preprocessed and stored in a structured database. The proposed model architecture combines a feature extraction module using convolutional neural networks (CNNs), a temporal dynamics module employing Long Short-Term Memory (LSTM) networks, and a regulatory attention layer designed to align predictions with compliance benchmarks. The dedicated compliance and liability-aware modules encode ISO, ISI, and domain-specific rules to ensure outputs adhere to permissible limits for biodegradability, shelf life, and environmental claims. Model training and optimization help in training, evaluating, and fine-tuning the model, and the final output of the process is a predictive model that helps predict the material behavior.

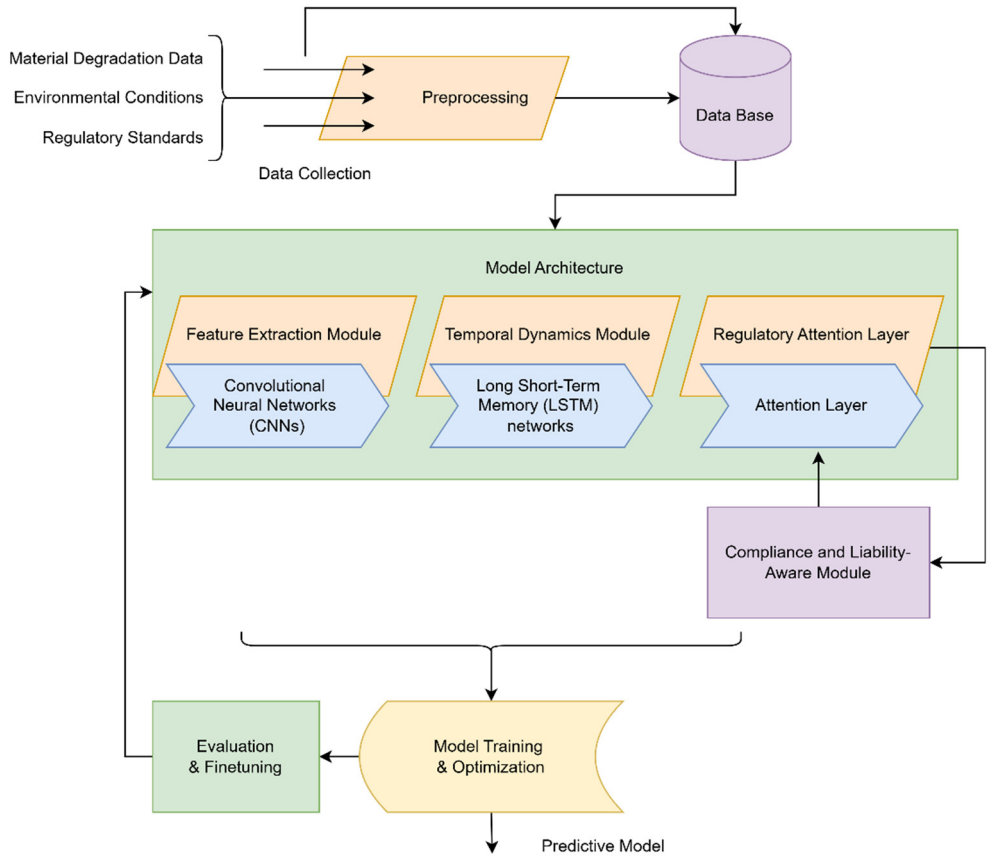


Figure 1. Methodology used in the study.

2.1. Data Collection and Preprocessing

The dataset used in the study integrates experimental degradation data captured from biodegradable materials, environmental exposure parameters, and regulatory benchmarks. The gathered data from multiple sources is then preprocessed and stored in a database for downstream analysis and modeling.

- Material degradation data—captured from the historical records of controlled biodegradation experiments. The study gathered data from ISO 14855-1 [15], composting tests and ASTM D5338 [16], aerobic degradation, and it includes information on weight loss, CO_2 evolution, and disintegration levels of polymers.
- Environmental conditions—gathers data such as temperature, humidity, pH, oxygen concentration, and microbial population density from simulation study environments and field studies.
- Regulatory standards—the compliance guidelines and related information extracted from ISO, ISI, and EU directives, as well as FDA guidelines. We obtain the required parameters for biodegradable percentages, maximum shelf-life, and environmental labeling limits.

The compiled dataset consisted of approximately 1250 degradation samples derived from 18 distinct biodegradable polymer formulations, including PLA, PCL, starch-based blends, and cellulose derivatives. The data were aggregated from a combination of publicly available experimental reports, literature-mined datasets compliant with ISO 14855 and ASTM D5338 standards, and curated environmental simulation datasets. Each material was evaluated under multiple physicochemical conditions, resulting in over 9000 time-series degradation data points. Regulatory thresholds were extracted from publicly available ISO, EU, and FDA documentation and encoded as structured compliance parameters within

the database. The dataset represents a heterogeneous but controlled experimental corpus designed to support both predictive modeling and compliance validation.

The collected data is preprocessed using basic preprocessing, feature engineering, and encoding. Techniques, including normalization and categorical encoding, are used to scale and encode the data; missing data for various parameters are calculated and treated accordingly, with alignment and mapping of multiple datasets into a common space.

2.2. Model Architecture

The captured data is processed and analyzed using a hybrid deep-learning framework designed to predict material degradation rates, with special attention given to the regulatory compliance for sustainable degradation of materials. The framework has three main layers/modules associated, which include the following:

- Feature extraction module—uses CNN to capture the spatial correlation between the various material degradation features, such as surface erosion patterns and microstructural changes.
- Temporal dynamics module—uses LSTM to identify and capture data for the temporal progression of material breakdown in various environmental conditions.
- The regulatory attention layer introduces an attention mechanism that helps prioritize features that are relevant for matching compliance and is dependent on the thresholds derived from ISO and ISI standards and constraints.

The architecture of the proposed model consists of multi-modal feature embeddings in the input layer, which will be processed by CNN layers to generate feature maps for indicators, while the associated LSTM layers help with the modeling of degradation curves and the attention layers help with regulatory compliance and prioritization. The fully connected layer finally helps predict the degradation percentage and compliance class.

2.2.1. Compliance and Liability-Aware Module

The proposed model has a compliance module, which is designed to analyze reliability and compliance with the regulatory frameworks and thresholds set by them. The module has a rule encoding where the guidelines from the standard are translated into logical constraints. Dynamic monitoring helps verify predictions and ensures that compliance is followed. The module will also be able to generate alerts on the real-time monitoring of the compliance of constraints employed.

2.2.2. Regulatory Attention Mechanism Formalization

Unlike conventional attention mechanisms that learn feature relevance solely based on predictive optimization, the proposed regulatory attention layer incorporates compliance-aware weighting. Regulatory constraints are implemented as soft penalty functions integrated into the composite loss formulation, rather than strict hard-rule elimination. Specifically, predicted degradation values that exceed permissible thresholds, e.g., <90% biodegradation within 180 days under ISO 14855 conditions, incur an additional regulatory penalty term.

The total loss function is expressed as:

$$L_{total} = L_{MSE} + \lambda_1 L_{CE} + \lambda_2 L_{reg}$$

where L_{reg} represents deviation from encoded compliance thresholds.

This design enables the network to remain flexible and data-driven while discouraging outputs that conflict with regulatory standards. Thus, the regulatory attention

layer acts as a compliance-guided weighting mechanism rather than a purely data-learned saliency layer.

2.3. Model Training and Optimization

The model training was performed using a supervised learning approach. We have used Mean Squared Error (MSE) for evaluating the performance of degradation levels, Cross-Entropy Loss functions for compliance classification, and Penalty Loss function for regulatory predictions and compliance mapping for permissible thresholds. We also have used Adam optimizer for the model learning rate of 1×10^{-4} and dropout layers (rate = 0.3), and L2 weight decay is applied to prevent overfitting. The 70% data was used for training, 15% for validation, and 15% for testing. Early stopping was used on the validation loss. The training was performed on a batch size of thirty-two, trained for one hundred epochs. The model performance was assessed using regression metrics—RMSE, MAE, and R2 score—for evaluating the prediction results. The classification results were evaluated based on Precision, Recall, and F1-score. We have also tested the effectiveness of the proposed model with comparisons to Random Forest, Gradient Boosting, and kinetic regression models.

To ensure robustness, all experiments were conducted over five independent runs with randomized train–validation–test splits, and the reported RMSE, MAE, and R^2 values represent mean performance across runs. The observed standard deviation for RMSE was $\pm 0.21\%$, indicating stable convergence behavior. This repeated evaluation approach reduces the risk of performance overestimation associated with single split reporting.

3. Results and Discussion

3.1. Predictive Performance of Models

The predictive accuracy of the proposed framework was benchmarked against conventional and machine learning models. As shown in Table 1 and Figure 2, the hybrid CNN–LSTM architecture with the regulatory attention layer achieved the lowest RMSE (3.8%) and MAE (2.6%), significantly outperforming kinetic regression and tree-based methods. The R^2 score of 0.95 further demonstrates the ability of the model to capture nonlinear interactions and long-term temporal dependencies in biodegradation data.

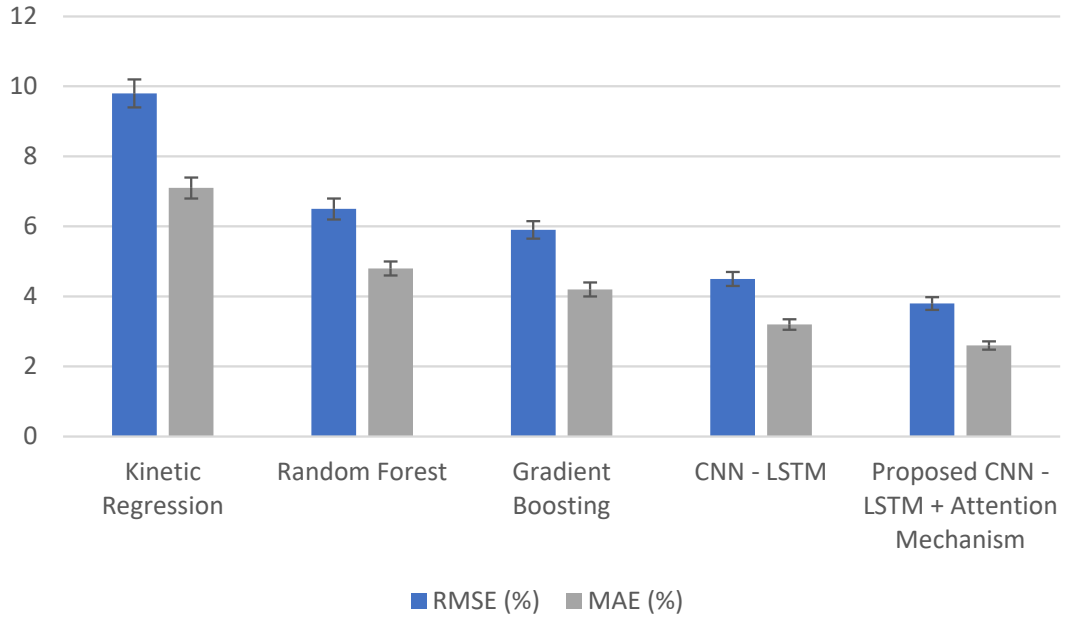


Figure 2. Comparative performance of baseline and proposed models using RMSE and MAE.

Table 1. Predictive performance comparison.

Model	RMSE (%)	MAE (%)	R^2
Kinetic Regression	9.8	7.1	0.78
Random Forest	6.5	4.8	0.86
Gradient Boosting	5.9	4.2	0.88
CNN–LSTM	4.5	3.2	0.92
Proposed CNN–LSTM + Attention Mechanism	3.8	2.6	0.95

3.2. Compliance Validation Across Industries

The model flagged non-compliant cases where degradation rates or shelf-life claims did not align with standards such as ISO 14855 or FDA guidelines. As seen in Table 2, compliance accuracy across the three tested sectors—packaging, healthcare, and consumer goods—ranged between 90% and 94%, indicating promising generalization potential across heterogeneous test conditions. Figure 3 shows the graphical visualization of the compliance validation results observed in the current study.

Table 2. Compliance validation results.

Industry	Compliance Accuracy (%)	Non-Compliant Cases (Flagged)
Packaging	91	3
Healthcare	94	1
Consumer Goods	90	4

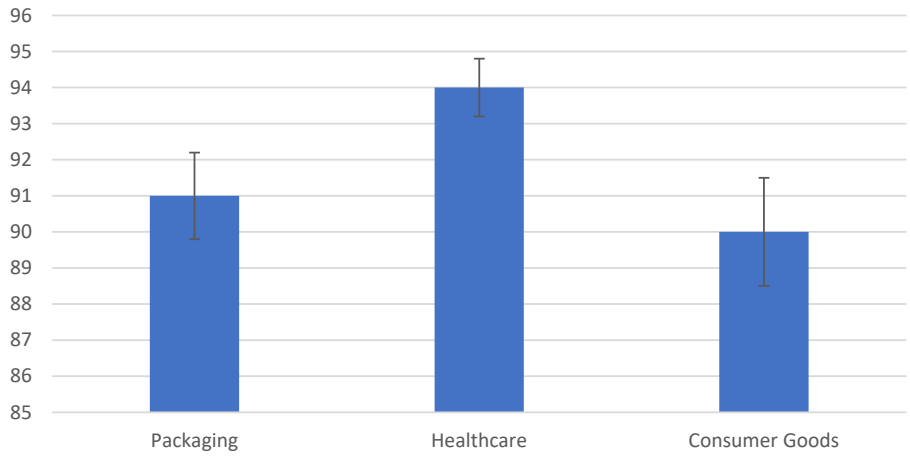


Figure 3. Compliance validation accuracy across industrial applications.

In packaging, the starch-based films showed reliable predictions of composting behavior, improving eco-labeling accuracy, and reducing risks of false green claims. In healthcare, polycaprolactone implants exhibited degradation predictions consistent with clinical safety standards, minimizing liability in medical applications. In consumer goods, cellulose-based items demonstrated variable degradation under aquatic conditions.

The integration of regulatory and liability-aware mechanisms significantly strengthens the trustworthiness and potential applicability in industrial decision-support contexts like predictive biodegradation models. While traditional models often optimize for accuracy alone, the proposed system balances predictive precision with compliance monitoring, thereby reducing risks of greenwashing and liability exposure. From a sustainability perspective, this approach enhances life cycle assessment accuracy, supporting policymakers in waste management and circular economy initiatives. From an industrial standpoint, the

ability to automatically flag non-compliance enables proactive risk mitigation, ensuring that product claims are scientifically valid, legally defensible, and ethically transparent.

4. Conclusions

This current study presents a DL framework for the prediction of biodegradable material degradation with integrated regulatory and liability-aware mechanisms within the modeling process. The framework combines material degradation data, environmental conditions, and microbiological interactions with international standards such as ISO and ISI guidelines. The proposed CNN–LSTM model integrates a regulatory attention layer and has achieved high predictive accuracy and efficient compliance validation. The results demonstrated that the model outperforms conventional approaches in terms of evaluation metrics, including RMSE, MAE, and R^2 scores. The predicted output remains within permissible thresholds for eco-labeling, shelf-life claims, and environmental compliance. The study experimented with packaging, healthcare, and consumer goods industries, highlighting the practical value of embedding liability-aware checks, which reduce the risk of false claims and strengthen consumer trust.

The proposed methodology contributes to sustainable material design and supports life cycle assessment, offering industries and regulators a reliable tool for balancing innovation, environmental responsibility, and legal accountability. The work also demonstrates that embedding regulatory and ethical considerations directly into AI-driven models enhances their technical performance and societal relevance. Future work will focus on expanding the dataset to include multi-modal inputs such as imaging and spectroscopy data, extending compliance integration to cover a wider range of global regulatory frameworks, and testing the model in real-world industrial pipelines to further strengthen the role of intelligent systems in enabling sustainable, compliant, and trustworthy biodegradable material solutions.

The present study is based on curated experimental and simulation-supported datasets, and while the results indicate promising performance, further validation using large-scale industrial deployment data is necessary. Additionally, regulatory encoding is currently focused on selected ISO and domain-specific frameworks; expansion to multi-jurisdictional regulatory systems remains a future objective.

Author Contributions: Conceptualization, S.B. and K.P.; methodology, S.B.; software, S.B.; validation, S.B., K.P. and S.S.; formal analysis, S.B.; investigation, S.B.; resources, S.B.; data curation, S.B.; writing—original draft preparation, S.B.; writing—review and editing, S.B.; visualization, S.B.; supervision, S.S.; project administration, S.B. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The raw data supporting the conclusions of this article will be made available by the authors on request.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

DL	Deep Learning
CNN	Convolutional Neural Networks
LSTM	Long Short-Term Memory

ISO	International Organization for Standardization
ISI	Indian Standards Institution (now Bureau of Indian Standards)
pH	Power of Hydrogen
EU	European Union
FDA	Food and Drug Administration
MSE	Mean Squared Error
RMSE	Root Mean Square Error
MAE	Mean Absolute Error

References

1. Nash, W.; Drummond, T.; Birbilis, N. A review of deep learning in the study of materials degradation. *NPJ Mater. Degrad.* **2018**, *2*, 37. [CrossRef]
2. Atik, I. Analysis of Biodegradable and Non-Biodegradable Materials Using Selected Deep Learning Algorithms. *Int. J. Comput.* **2022**, *45*, 48–59.
3. Mndlovu, H.; Kumar, P.; du Toit, L.C.; Choonara, Y.E. A review of bio material degradation assessment approaches employed in the biomedical field. *NPJ Mater. Degrad.* **2024**, *8*, 66. [CrossRef]
4. Pandey, S.K.; Pore, S.; Roy, K. Assessing biodegradability potential of organic chemicals in aquatic and soil environment through classification-based machine learning models developed in accordance with OECD standards. *Sci. Total Environ.* **2025**, *1000*, 180376. [CrossRef] [PubMed]
5. Samir, A.; Ashour, F.H.; Hakim, A.A.A.; Bassyouni, M. Recent advances in biodegradable polymers for sustainable applications. *NPJ Mater. Degrad.* **2022**, *6*, 68. [CrossRef]
6. Yu, Y.; Flury, M. Unlocking the potentials of biodegradable plastics with proper management and evaluation at environmentally relevant concentrations. *NPJ Mater. Sustain.* **2024**, *2*, 9. [CrossRef]
7. Filiciotto, L.; Rothenberg, G. Biodegradable plastics: Standards, policies, and impacts. *ChemSusChem* **2021**, *14*, 56–72. [CrossRef] [PubMed] [PubMed Central]
8. Zhang, J.; Norinder, U.; Svensson, F. Deep learning-based conformal prediction of toxicity. *J. Chem. Inf. Model.* **2021**, *61*, 2648–2657. [CrossRef] [PubMed]
9. Khanam, M.M.; Uddin, M.K.; Kazi, J.U. Advances in machine learning for the detection and characterization of microplastics in the environment. *Front. Environ. Sci.* **2025**, *13*, 1573579. [CrossRef]
10. Romeiko, X.X.; Zhang, X.; Pang, Y.; Gao, F.; Xu, M.; Lin, S.; Babbitt, C. A review of machine learning applications in life cycle assessment studies. *Sci. Total Environ.* **2024**, *912*, 168969. [CrossRef]
11. Brydon, L.; Zhang, K.; Dobbie, G.; Taškova, K.; Wicker, J.S. Predictive modeling of biodegradation pathways using transformer architectures. *J. Cheminformatics* **2025**, *17*, 21. [CrossRef] [PubMed]
12. Lindberg, S.; Hansen, E. Machine Learning for Predicting Performance and Degradability of Bio-Based Food Packaging. *Front. Chem. Mater. Catal.* **2025**, *2*, 1–9. [CrossRef]
13. Gbadago, D.Q.; Hwang, G.; Lee, K.; Hwang, S. Deep Learning for Green Chemistry: An Ai-Enabled Pathway for Biodegradability Prediction and Organic Material Discovery. *Korean J. Chem. Eng.* **2024**, *41*, 2511–2524. Available online: https://ssrn.com/abstract=4689153 (accessed on 12 February 2025). [CrossRef]
14. Alhulaybi, Z.A.; Otaru, A.J. Machine learning analysis of enhanced biodegradable Phoenix dactylifera L./HDPE composite thermograms. *Polymers* **2024**, *16*, 1515. [CrossRef] [PubMed] [PubMed Central]
15. *ISO 14855-1:2005*; Determination of the ultimate aerobic biodegradability of plastic materials under controlled composting conditions—Method by analysis of evolved carbon dioxide—Part 1: General method. International Organization for Standardization: Geneva, Switzerland, 2005.
16. *ASTM D5338-15(2021)*; Standard Test Method for Determining Aerobic Biodegradation of Plastic Materials Under Controlled Composting Conditions, Including Thermophilic Temperatures. ASTM International: West Conshohocken, PA, USA, 2021.

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.