Review Article

Smart and Sustainable: Review of AI-Driven Approaches in Biodegradable Food Packaging Systems

Abstract

Biodegradable materials for food preservation are becoming more popular as a result of the growing need for environmentally friendly and sustainable packaging solutions. However, because biopolymers have a wide range of characteristics and behaviours, improving the sustainability, safety, and performance of such materials is still a difficult task. One promising way to speed up research and innovation in this field is through artificial intelligence (AI). The use of AI in the creation, formulation, and improvement of biodegradable packaging systems is examined in this review. Predicting material properties, designing polymer blends in reverse, integrating sensors into smart packaging, and automated quality control are some of the main uses. Case studies demonstrating effective applications of machine learning and deep learning methodologies in actual biodegradable packaging situations are also covered in the review. Limitations are also critically analysed, including regulatory barriers, model interpretability, and data scarcity. The study concludes by outlining potential future developments, highlighting how AI-driven technologies, digital twins, and autonomous labs could revolutionise the sustainable packaging sector. This review offers a thorough grasp of how AI can facilitate the shift to intelligent, secure, and environmentally friendly food packaging systems by highlighting recent developments and potential future paths.

التعليق [MF1]: behaviors

التعليق [MF2]: analyzed

Keywords: Artificial Intelligence, Biodegradable Packaging, Food Preservation, Sustainable Packaging, Biopolymers

Introduction

Artificial intelligence, commonly shortened to AI, generally refers to any computational discipline that attempts to replicate or simulate what people broadly describe as intelligence, judgment, or memory [1, 2]. Within that expanse, observers usually draw a line between weak AI, which is content to behave as if it understands, and strong AI, which claims to actually share the cognitive architecture of a human mind [3]. The latter remains little more than a research ambition; no system in operation today is widely accepted as passing that philosophical threshold. Nonetheless, practical applications spring up in strikingly diverse contexts, from videogames and meteorology to assembly-line robotics and medical imaging [4-11]. Each setting takes advantage of techniques that range from reinforcement learning and fuzzy logic to swarm intelligence and rule-based expert systems [3]. Developers favor these tools because they tend to lower costs, sharpen product quality, and boost the bottom line [7, 12].Food consumption is expected to increase from 59% to 98% by 2050 due to the world's growing population [13]. AI has therefore been used in a variety of fields to meet this need for food, including supply chain management, food sorting, manufacturing development, food quality enhancement, and appropriate industrial hygiene [14–16]. According to Sharma, at least until 2021, the food processing and handling sectors are anticipated to expand at a CAGR of roughly 5% [15]. According to Funes and colleagues [17], ANN has been employed as a tool to help solve genuine complex problems in the food business. Correa et al. claim that ANN makes parameter classification and prediction easier, which has increased ANN utilisation demand in recent years.[18]

1. Overview of Biodegradable Packaging Materials

The food industry is seeing an increase in demand for biodegradable packaging due to the environmental impact of traditional plastic packaging, which is mostly made from non-renewable petrochemical sources. By allowing microorganisms to break down naturally into water, carbon dioxide (or methane), and biomass, biodegradable packaging materials can reduce ecological harm and pollution in the environment. Usually, renewable biomass sources like proteins, polysaccharides, and microbial polyesters are used to make these materials.

A. PLA, or polylactic acid

One of the most popular biodegradable polymers for food packaging is PLA. It is made from renewable resources, such as sugarcane or maize starch, by fermentation of lactic acid and then polymerising it. PLA has limited barrier qualities and low heat resistance, but it has good mechanical strength and transparency[19].

B. Starch-Based Films

Starch is cheap, plentiful, and biodegradable. Gelatinisation and film-forming methods are used to create starch-based films. Nevertheless, their poor water vapour resistance is caused by their high hydrophilicity. Flexibility and performance can be improved by blending with additional biopolymers or by using plasticisers like glycerol[20].

C. Cellulose and Derivatives

The most prevalent natural polymer, cellulose, is taken from plant or wood fibres. Cellulose films have good gas barrier qualities, transparency, and tensile strength. Methylcellulose and carboxymethylcellulose derivatives improve the ability to form films and are frequently used in coatings[21]

D. Chitosan

Chitin, which is typically obtained from shellfish waste, is the precursor to chitosan. Because of its innate antimicrobial and antifungal properties, it can be used in active food packaging. Because of its good film-forming qualities, chitosan films are frequently mixed with nanoparticles or essential oils to improve functionality[22].

E. Protein-Based Films

Whey, soy, and gelatin are some of the proteins that can be used to make biodegradable films because they can form films and stop gas from getting through. But protein films don't work well on their own because they are sensitive to moisture and need to be cross-linked or mixed with other polymers[23].

F. Polyhydroxyalkanoates (PHAs)

Bacteria make PHAs, which are microbial polyesters, when there aren't enough nutrients. The most studied type is polyhydroxybutyrate (PHB). PHAs are more expensive than other biodegradable polymers, but they do a good job of keeping moisture and oxygen out[24].

3. Role of Artificial Intelligence in Material Science

Artificial Intelligence (AI) is changing the field of material science by speeding up the discovery of new materials, improving the conditions for processing them, and forecasting how they will perform. This section talks about how different AI techniques, like machine learning (ML), deep learning (DL), and data-driven modelling, are changing the old way of doing things through trial and error into a process that is more predictable and efficient.

A. AI for Accelerated Material Discovery

AI algorithms help find new materials with the right properties by looking at big sets of data and making predictions about which ones are most likely to work without having to do a lot of lab tests.

Using ML models for high-throughput screening lets you quickly test out possible combinations of materials.

Bayesian optimization methods improve the selection of candidates by concentrating on the design space's most promising areas [25,26].

B. Prediction of Material Properties

Using simulation or empirical data, machine learning models can be trained to forecast the mechanical, chemical, thermal, and physical characteristics of materials. This is especially helpful when creating biodegradable packaging with particular mechanical or barrier properties.

For property prediction, supervised learning algorithms—such as decision trees and support vector machines—are employed.

Model accuracy is improved through feature engineering based on material microstructure or molecular descriptors [27,28]

C. Process Optimization in Material Synthesis

During synthesis or fabrication, AI helps determine the ideal processing parameters, including temperature, pressure, time, and chemical composition. This enhances the consistency and quality of the material.

For multivariate optimisation tasks, genetic algorithms (GAs) and reinforcement learning (RL) are commonly employed.

AI improves extrusion, film casting, and coating techniques in the processing of biodegradable polymers[29,30].

D. Microstructure Analysis and Image Recognition

Quality control and defect detection are aided by the automated analysis of material microstructures from microscopy images made possible by deep learning techniques, particularly convolutional neural networks (CNNs).

AI is able to quantify porosity or dispersion in composite films, identify grain boundaries, and classify crystal structures[31,32].

E. Virtual Screening and Materials Informatics

Virtual screening of thousands of compounds for specific applications is made possible by AI in conjunction with materials informatics and databases such as Materials Project, AFLOW, and OQMD.

When choosing sustainable, safe packaging materials, these tools help make well-informed decisions[33,34].

F. Data Extraction from Scientific Literature

Experimental data, synthesis pathways, and material properties are automatically extracted from thousands of journal articles and patents using Natural Language Processing (NLP) techniques.

This speeds up knowledge discovery and greatly enhances AI training datasets[35].

G. Sustainability and Lifecycle Modeling

By incorporating life-cycle assessment (LCA) data, artificial intelligence (AI) can also be used to model the environmental effects and biodegradation potential of packaging materials.

It encourages the creation of environmentally friendly and functional packaging[36].

4. AI Applications in Biodegradable Packaging

The development of biodegradable packaging through the application of artificial intelligence (AI) has become a game-changer for the food sector. AI enables more intelligent formulation, performance prediction, design optimisation, and sustainability analysis of biodegradable materials by utilising sophisticated algorithms. An extensive summary of the main AI applications in this field can be found below.

a. Formulation and Material Selection

The best biopolymer blends, plasticisers, and functional additives to improve the mechanical, thermal, and barrier qualities of biodegradable films are found with the help of AI algorithms.

The compatibility of cellulose-based polymers, PLA, chitosan, and starch with various additives is predicted by machine learning (ML) models like random forests and support vector machines.

Inverse design, in which ideal formulations are predicted by entering desired properties, is made possible by AI[37].

b. Prediction of Film Properties

AI models forecast important material attributes like

- Young's modulus, elongation at break, and tensile strength

- Oxygen transmission rate (OTR) and water vapour permeability (WVP)
- Kinetics of degradation in diverse environmental settings

Extensive experimental trials are not as necessary with these models.

c. Structural Design Optimization

AI can simulate and optimize packaging design parameters such as:

- Thickness, layer arrangement, and porosity
- Surface coating uniformity
- Nanoparticle dispersion in bio-nanocomposites

Advanced algorithms like **genetic algorithms (GAs)** and **topology optimization** methods help design films with enhanced performance using minimal resources.

d. Shelf Life and Spoilage Prediction

Deep learning and sensor-integrated neural networks are two examples of AI models that are used to:

Anticipate patterns of food deterioration and microbial spoiling.

Make the best packaging material recommendations based on environmental factors and perishability.

Control intelligent packaging systems that keep an eye on gases, humidity, and temperature[38].

e. Sustainability and Environmental Impact Modeling

AI helps with eco-efficiency modelling and life cycle assessment (LCA) by:

- Calculating the biodegradation time and carbon footprint
- Forecasting recyclability and end-of-life behaviour
- Logistics optimisation for a low environmental impact

Strategies for developing sustainable packaging are guided by these insights[39]

f. Quality Control and Defect Detection

Applications of AI in quality control include:

- Convolutional neural networks (CNNs) and computer vision for visual inspection
- Real-time detection of film homogeneity, coating irregularities, and surface cracks

These systems decrease production waste and increase consistency.

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5. Case Studies and Research Advances

Case Study	**AI Technique Used**	**Application Area**	**Biodegradable Material**
Case Study 1	Machine Learning (Random Forest, Decision Trees)	Property prediction (e.g., tensile strength, water vapor permeability)	Starch-based films
Case Study 2	Inverse Design using Machine Learning	Formulation optimization	PLA-based blends
Case Study 3	Deep Learning with Sensor Integration	Food spoilage detection in real time	Smart biodegradable film with sensors
Case Study 4	Convolutional Neural Networks (CNNs)	Automated defect detection during film production	PLA–starch composite films
Case Study 5	Multi-objective AI Optimization	Antimicrobial packaging formulation	Chitosan with natural additives

Table 1. Case Studies and Research Advances

Recent studies show how artificial intelligence (AI) can be used practically in biodegradable packaging. These studies show how artificial intelligence (AI) methods like computer vision, deep learning, and machine learning are being used to improve sustainability analysis, performance prediction, smart packaging integration, and material design.

a. **Predictive Modeling for Film Properties**
   In order to forecast the mechanical and barrier characteristics of starch-based films, [40] used machine learning algorithms, such as decision trees and random forests. Their model reduced the number of necessary physical experiments by accurately estimating tensile strength, elongation at break, and water vapour permeability based on ingredient composition and processing parameters.
b. **Inverse Design of PLA-Based Films**
   An AI-powered inverse design framework for PLA-based biodegradable films was presented by [41]. In order to attain desired performance metrics such as mechanical strength, barrier qualities, and biodegradability, their machine learning model forecasted the best polymer combinations and additive concentrations.
c. **Smart Packaging with AI for Spoilage Detection**
   In order to detect spoilage in perishable foods, [42] created an AI-integrated smart packaging system that combines deep learning algorithms with biosensors. By effectively classifying food freshness levels from real-time sensor data, the model decreased food waste and enhanced supply chain security.
d. **Quality Control Using Computer Vision**
   Convolutional neural networks (CNNs) were employed by [43] to identify manufacturing flaws in PLA-starch biodegradable films. During production, the automated image-based inspection system found problems like pinholes, cracks, and inconsistent thickness, improving quality control and reducing material waste.
e. **AI for Life Cycle and Sustainability Assessment**
   [44] forecasted the environmental effects of biopolymer-based packaging materials over their life cycle using machine learning models. This method made it possible to quickly assess resource usage and carbon footprints, facilitating data-driven choices for the creation of sustainable packaging.
f. **Optimization of Antimicrobial Packaging**
   In order to optimize the composition of chitosan films infused with essential oils for antimicrobial packaging, [45] used AI models. The shelf life of fresh produce was increased by the AI-optimized formulations, which also enhanced film flexibility and microbial inhibition.

6. Limitations and Challenges

Although there are many potential benefits to incorporating artificial intelligence (AI) into biodegradable packaging research and development, a number of restrictions and difficulties prevent its broad use and best use. For AI to realise its full potential in this field, these issues—which are caused by technical, data-related, financial, and regulatory factors—must be resolved.

a. **Data Availability and Quality**
   The lack of extensive, high-quality, domain-specific datasets is a major barrier to AI-driven research on biodegradable packaging. The composition, source, and performance characteristics of biodegradable materials vary greatly, but the majority of the data that is currently available is fragmented, inconsistent, or proprietary. Effective model training and validation are hampered by the absence of comprehensive open-access databases and standardised experimental protocols [46].
b. **Complexity of Material Behavior**
   Non-linear, multi-variable interactions between polymers, additives, environmental factors, and degradation pathways are frequently seen in biodegradable materials. It is still difficult to capture

this complexity using traditional machine learning models, particularly when the physical mechanisms are poorly understood or there is insufficient data [47]. Because of this, AI models might not be as interpretable or generalisable to other material systems.

c. Lack of Interdisciplinary Expertise

Successful implementation of AI in packaging requires **collaboration between material scientists, data scientists, and food technologists**. However, many research teams lack the necessary cross-disciplinary expertise, leading to either technically sound AI models that are poorly grounded in material science, or material-focused research that underutilized modern AI techniques [48].

d. Economic and Computational Costs

Many academic or small industrial settings may lack the computational resources and technical infrastructure necessary for the development, training, and validation of AI models, particularly those involving deep learning or ensemble techniques. Furthermore, experimental validation for AI-recommended formulations can be expensive, particularly if testing is needed for a variety of food types or storage conditions [49].

e. Model Interpretability and Transparency

Models need to be interpretable in order for AI adoption in the food packaging industry to gain credibility, particularly in situations where safety or regulations are at stake. Nevertheless, a lot of powerful AI models (like deep neural networks) function as "black boxes," making it challenging to justify the reasoning behind specific formulations or design suggestions. Their application in crucial decision-making and compliance procedures may be hampered by this lack of transparency [50]

f. Regulatory and Ethical Concerns

Innovations in packaging powered by AI frequently surpass current regulatory frameworks. Legal and moral dilemmas pertaining to food safety, labelling, or environmental claims may arise from unclear regulations governing AI-generated content or judgements. In order to maintain credibility and public trust, third-party certification or auditing may be necessary for the use of AI in sustainability assessments [51].

7. Future Perspectives

It is expected that as AI technology advances, its application to the field of biodegradable food packaging will become more profound. A more data-driven, sustainable, and networked approach to packaging innovation is suggested by emerging trends and research avenues.

a. Creation of Unified AI–Material Databases

The future of AI in material science depends heavily on **well-structured, open-access datasets**. Current efforts are fragmented, but future initiatives are expected to promote standardized experimental protocols and curated datasets for biodegradable polymers, facilitating high-fidelity model training and comparison [52].

b. Digital Twin Technology for Packaging Design

By simulating the behaviour of packaging materials in real time under different conditions, digital twins—virtual copies of physical systems—allow for iterative design improvements prior to physical prototyping. AI-trained digital twins could be used in future packaging labs to expedite material optimisation and discovery [53].

التعليق [MF3]: behavior

التعليق [MF4]: optimization

c. AI-Driven Biopolymer Design with Sustainability Metrics

It is anticipated that future AI models will incorporate social, economic, and environmental sustainability metrics into algorithms for material optimisation. This will guarantee that packaging materials are both practical and in line with more general environmental objectives [54].

d. Federated Learning for Industrial Collaboration

Industries may be able to train predictive models on sensitive material data using federated learning, a decentralised AI training technique, without disclosing proprietary formulations. This will preserve intellectual property rights and promote cooperation across industries [55].

التعليق [MF5]: decentralized

e. Robotics and AI in Autonomous Packaging Labs

The development of "self-driving laboratories" that create and test biodegradable packaging films on their own may result from the combination of AI, robotics, and automation. These labs can speed up time-to-market and drastically cut down on development cycles [56].

f. Integration of AI with Biodegradation Simulations

The prediction of actual packaging biodegradation behaviour under various environmental conditions may be aided by AI-based modelling of microbial activity, enzymatic degradation, and composting conditions [57].

التعليق [MF6]: behavior

g. Ethical AI Frameworks for Green Technology

The need for morally sound, open, and comprehensible models is increasing as AI is used to make decisions in sustainability evaluations. To guarantee that decisions pertaining to environmental impacts are reasonable and auditable, regulatory frameworks and ethical AI design principles will become crucial [58].

Conclusion

The intersection of artificial intelligence and biodegradable packaging represents a transformative shift in how sustainable food preservation solutions are developed, optimized, and deployed. AI offers powerful tools for material selection, property prediction, smart packaging integration, and life cycle assessment—enabling faster innovation cycles and data-driven design decisions. Despite challenges such as limited data availability, model transparency issues, and regulatory constraints, ongoing advancements in machine learning, automation, and interdisciplinary collaboration are steadily overcoming these barriers. Looking ahead, the adoption of AI in this field is expected to drive not only technical efficiency but also environmental responsibility, paving the way for intelligent, safe, and eco-friendly packaging systems that align with global sustainability goals.

COMPETING INTERESTS DISCLAIMER:

Authors have declared that they have no known competing financial interests OR non-financial interests OR personal relationships that could have appeared to influence the work reported in this paper.

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