

A Comprehensive Survey of Polymer Detection Techniques and Computer-Based Analysis Methods for Advanced Material Characterization

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Abstract

Polymers are widely used in aerospace, automotive, biomedical, packaging, electronics, and manufacturing industries because of their lightweight nature, durability, and versatility. Accurate polymer identification and characterization are essential for quality control, recycling, performance assessment, and the development of advanced materials. Characterization helps determine important properties such as chemical composition, molecular structure, thermal stability, mechanical strength, and surface morphology, which influence material performance and application suitability. Traditional polymer detection methods include Fourier Transform Infrared Spectroscopy (FTIR), Raman Spectroscopy, Nuclear Magnetic Resonance (NMR), Scanning Electron Microscopy (SEM), Differential Scanning Calorimetry (DSC), and Thermogravimetric Analysis (TGA). These techniques provide reliable and detailed information about polymer properties but often require expensive equipment, specialized expertise, and significant processing time. Recent advances in computer-based analysis, machine learning, and artificial intelligence have significantly improved polymer characterization and classification. Intelligent algorithms can automatically identify polymer types, predict material properties, detect defects, and analyze complex datasets with high accuracy. Machine learning models such as Support Vector Machines, Random Forests, and Deep Neural Networks enable faster and more efficient analysis compared to conventional methods. This survey reviews both traditional polymer detection techniques and emerging computational approaches. It discusses their working principles, advantages, limitations, and applications while highlighting current challenges and future research opportunities in AI-driven polymer analysis and material informatics.

Keywords: Nuclear magnetic resonance, machine learning, vector machines, polymeric materials and polymer characterization

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INTRODUCTION

The increasing utilization of polymeric materials has created a growing demand for efficient detection, classification, and characterization techniques. Conventional analytical methods provide accurate material identification but often require expensive instrumentation, extensive sample preparation, and expert interpretation. Recent developments in computer vision, machine learning, deep learning, and explainable artificial intelligence have transformed polymer analysis by enabling automated and data-driven decision-making processes. This survey examines both traditional and computational approaches for polymer detection and analysis.

Recent studies have demonstrated the growing

importance of machine learning and data-driven approaches in polymer composite research [1]. Recent reviews have emphasized the role of machine learning in property prediction, material optimization, and intelligent manufacturing of polymer composites. Advanced techniques such as artificial neural networks, support vector machines, convolutional neural networks, and polymer informatics frameworks have shown significant potential for predicting mechanical, thermal, electrical, and flammability properties [2]. Furthermore, explainable artificial intelligence and multi-objective optimization methods are emerging as promising tools for enhancing model transparency and accelerating polymer material discovery [3].

TRADITIONAL POLYMER DETECTION TECHNIQUES

Fourier Transform Infrared Spectroscopy (FTIR)

FTIR is one of the most widely used techniques for polymer identification.

Advantages

- Non-destructive analysis
- High chemical specificity
- Rapid identification

Limitations

- Limited effectiveness for complex mixtures
- Requires spectral databases

Raman Spectroscopy

Raman spectroscopy analyzes molecular vibrations to identify polymer structures.

Applications

- Polymer classification
- Microplastic detection
- Composite material characterization

Nuclear Magnetic Resonance (NMR)

NMR provides detailed information about polymer molecular structure.

Advantages

- High structural accuracy
- Molecular-level characterization

Limitations

- Expensive instrumentation
- Complex data interpretation

X-Ray Diffraction (XRD)

Used to determine crystallinity and phase composition of polymers.

Thermal Analysis Techniques

- Differential Scanning Calorimetry (DSC)
- Thermogravimetric Analysis (TGA)
- Dynamic Mechanical Analysis (DMA)

These techniques evaluate thermal stability and mechanical behavior.

Table 1. Common algorithms.

Algorithm	Applications
Random Forest	Property prediction
SVM	Polymer classification
ANN	Mechanical property estimation
XGBoost	Performance optimization
Gradient Boosting	Composite analysis

Microscopy-Based Polymer Analysis

- Optical Microscopy
- Used for surface inspection and defect analysis.
- Scanning Electron Microscopy (SEM)

Sem Provides High-Resolution

- Fiber dispersion
- Surface morphology
- Crack propagation
- Composite interfaces

Transmission Electron Microscopy (TEM)

Used for nanoscale polymer and nanoparticle characterization.

Computer Vision-Based Polymer Detection

Recent advancements have enabled automatic polymer identification using images.

Workflow

1. Image Acquisition
2. Image Preprocessing
3. Feature Extraction
4. Classification
5. Performance Evaluation

Extracted Features

- Texture features
- Shape descriptors
- Color features
- Morphological characteristics

Algorithms

- Support Vector Machine (SVM)
- Random Forest
- K-Nearest Neighbor (KNN)
- Decision Tree

Machine Learning for Polymer Analysis

Machine learning enables predictive analysis of polymer properties.

Deep Learning Approaches

Convolutional Neural Networks (CNNs)

- Polymer image classification
- Defect detection
- Surface analysis

Recurrent Neural Networks (RNNS)

- Time-series polymer processing data
- Manufacturing process monitoring

Vision Transformers (ViTs)

Emerging technology for high-accuracy material image classification.

Spectroscopy and AI Integration

AI models can analyze:

- FTIR spectra
- Raman spectra
- NMR signals
- Thermal curves

Benefits Include

- Automated classification
- Reduced human intervention
- Faster analysis
- Improved accuracy

Artificial Intelligence (AI) and Machine Learning (ML) techniques have emerged as powerful tools for analyzing complex polymer characterization data. Modern AI models can process and interpret information obtained from multiple analytical techniques, including FTIR spectra, Raman spectra, NMR signals, and thermal analysis curves. These datasets often contain large amounts of information that can be difficult and time-consuming for researchers to analyze manually. By learning patterns from historical data, AI algorithms can automatically identify polymer types, classify material structures, and predict important material properties with high accuracy.

In FTIR and Raman spectroscopy, AI models can recognize characteristic spectral peaks and classify polymers based on their chemical composition. Similarly, machine learning algorithms as referred in table 1 can analyze NMR signals to identify molecular structures, functional groups, and polymer chain characteristics. Thermal analysis data obtained from techniques such as DSC and TGA can also be processed using AI methods to predict thermal stability, degradation behavior, crystallinity, and processing performance. Deep learning models, particularly Convolutional Neural Networks (CNNs), have shown excellent performance in extracting meaningful features from complex spectroscopic and thermal datasets without extensive manual feature engineering.

The integration of AI into polymer analysis offers several significant advantages. Automated classification reduces the need for extensive human expertise and minimizes subjective interpretation of results. AI-driven systems enable faster analysis by processing large datasets in a fraction of the time required by traditional methods. Furthermore, advanced algorithms can improve accuracy by detecting subtle patterns that may be overlooked during manual examination. These capabilities support real-time decision-making, enhance quality control processes, and accelerate material development. As AI technologies continue to evolve, they are expected to play an increasingly important role in intelligent polymer characterization and material informatics systems.

CHALLENGES IN POLYMER DETECTION AND COMPUTER-BASED ANALYSIS**Data Availability and Quality Challenges**

One of the major challenges in polymer analysis is the limited availability of high-quality and

standardized datasets. Experimental polymer characterization often requires expensive laboratory equipment and specialized expertise, resulting in relatively small datasets compared to those available in other machine learning domains. Additionally, variations in sample preparation, testing conditions, and measurement techniques can introduce inconsistencies and noise into the collected data [4]. These factors may reduce the reliability of predictive models and hinder their ability to generalize across different polymer systems.

Complexity of Polymer Structures

Polymers exhibit highly complex molecular architectures and diverse physical properties that are influenced by factors such as molecular weight, crystallinity, processing conditions, and filler composition. Capturing these intricate relationships using computational models is a significant challenge. The nonlinear interactions between polymer matrices, additives, and environmental conditions often make it difficult to develop accurate predictive models capable of representing real-world material behavior [1].

High-Dimensional and Heterogeneous Data

Polymer characterization involves data from multiple sources, including spectroscopy, microscopy, thermal analysis, mechanical testing, and sensor measurements. Integrating these heterogeneous datasets into a unified analytical framework is challenging due to differences in data formats, scales, and dimensionality. High-dimensional datasets may also increase computational complexity and introduce redundant or irrelevant features, thereby affecting model performance and interpretability [5].

Interpretability and Trustworthiness of AI Models

Although machine learning and deep learning models have demonstrated remarkable predictive capabilities, many operate as black-box systems that provide limited insight into their decision-making processes. In material science applications, understanding why a model produces a particular prediction is often as important as the prediction itself. The lack of transparency can reduce user confidence and limit the adoption of AI-driven approaches in industrial and research environments. Consequently, the integration of Explainable Artificial Intelligence (XAI) techniques remains an important area of ongoing research [6].

Computational Resource Requirements

Advanced machine learning and deep learning models frequently require substantial computational resources for training and optimization. Processing large-scale microscopy images, spectral datasets, and spatio-temporal material information may demand high-performance computing infrastructure, graphics processing units (GPUs), and significant storage capacity. These requirements can increase operational costs and limit accessibility for smaller research laboratories and industrial organizations [8].

Generalization Across Different Polymer Systems

A model trained on one type of polymer or composite material may not perform well when applied to other polymer families with different chemical compositions and structural characteristics [13]. Variations in manufacturing processes, environmental conditions, and reinforcement materials can significantly influence material behavior. Developing generalized models capable of accurately predicting properties across diverse polymer systems remains a challenging task for researchers [14].

Real-Time Monitoring and Processing Limitations

Modern manufacturing environments increasingly require real-time monitoring and quality assessment of polymer products. However, processing large volumes of sensors, image, and process data in real time presents significant technical challenges. Delays in data acquisition, feature extraction, and model inference may limit the effectiveness of intelligent monitoring systems, particularly in high-speed industrial production settings [7].

Integration with Industry 4.0 Environments

The implementation of AI-based polymer analysis systems within Industry 4.0 frameworks requires seamless integration with sensors, Internet of Things (IoT) devices, cloud platforms, and manufacturing execution systems. Ensuring interoperability, data security, and reliable communication among these components remains a major challenge. Furthermore, organizations must address concerns related to cybersecurity, data privacy, and system maintenance when deploying intelligent polymer monitoring solutions [9].

Standardization and Benchmarking Issues

The absence of universally accepted benchmarks and evaluation standards for polymer informatics makes it difficult to compare the performance of different machine learning models and analytical techniques. Variations in datasets, preprocessing methods [11], feature engineering strategies, and evaluation of metrics often lead to inconsistent results across studies. Establishing standardized protocols for data collection, model validation, and performance assessment is essential for advancing the field.

Sustainability and Environmental Considerations

As global attention shifts toward sustainable materials and circular economy practices, researchers face the challenge of developing analytical methods capable of efficiently identifying, classifying, and recycling polymer waste [12]. Detecting mixed polymer streams, microplastics, and degraded materials remains difficult due to their complex compositions and varying physical properties [1]. Future computer-based analysis systems must support sustainable material management while maintaining high levels of accuracy and efficiency.

Despite significant advances in polymer detection and computer-based analysis, challenges related to data quality, model interpretability, computational complexity, real-time processing, and industrial deployment continue to hinder widespread adoption. Addressing these limitations through explainable AI, multimodal data fusion, scalable computing infrastructures, and standardized evaluation frameworks will be crucial for the future development of intelligent polymer informatics systems [10].

FUTURE RESEARCH DIRECTIONS

Explainable Artificial Intelligence (XAI) for Polymer Informatics

Future research should focus on integrating Explainable Artificial Intelligence (XAI) techniques with polymer informatics frameworks to improve the transparency and interpretability of machine learning models. Methods such as SHAP, LIME, and attention-based mechanisms can help researchers understand the influence of material composition, processing parameters, and environmental conditions on polymer properties. Enhanced interpretability will increase trust in AI-driven predictions and facilitate their adoption in industrial applications.

Real-Time Polymer Monitoring and Smart Manufacturing

The development of real-time monitoring systems represents a promising research direction for polymer manufacturing. By combining sensors, machine learning algorithms, and Industrial Internet of Things (IIoT) technologies, future systems can continuously monitor polymer processing conditions and material quality. Such intelligent monitoring platforms can enable early defect detection, process optimization, and predictive maintenance, thereby improve production efficiency and reduce material waste.

Digital Twin Technology for Polymer Systems

Digital twins are virtual representations of physical materials and manufacturing processes. Future studies can explore the creation of digital twin models for polymer production environments, allowing researchers and engineers to simulate material behavior under different operating conditions. Digital twins can support process optimization, performance prediction, and lifecycle management while reducing the need for costly experimental trials.

Advanced Deep Learning Architectures

Although conventional machine learning methods have shown promising results, advanced deep learning architectures such as Convolutional Neural Networks (CNNs), Graph Neural Networks (GNNs), Transformers, and Vision Transformers (ViTs) offer significant potential for polymer analysis. These models can automatically learn complex spatial and structural patterns from microscopy images, spectral data, and molecular representations, leading to more accurate property prediction and material characterization.

Multimodal Data Fusion

Future polymer informatics systems should focus on integrating data from multiple characterization techniques, including FTIR, Raman spectroscopy, SEM, TEM, thermal analysis, and mechanical testing. Multimodal data fusion can provide a more comprehensive understanding of polymer behavior by combining complementary information from diverse sources. Such integrated approaches are expected to improve predictive accuracy and enhance decision-making capabilities.

Spatio-Temporal Data Analytics

Polymer properties often evolve over time due to aging, environmental exposure, thermal degradation, and mechanical loading. Future research should investigate spatio-temporal data mining techniques capable of analyzing both spatial and temporal variations in polymer systems. These approaches can support long-term performance prediction, reliability assessment, and durability analysis of advanced polymer composites.

AI-Driven Material Discovery and Design

Artificial Intelligence has the potential to accelerate the discovery of novel polymer materials with desired mechanical, thermal, and chemical properties. Future research may focus on generative models, reinforcement learning, and optimization algorithms to automatically design new polymer formulations and composite structures. This approach can significantly reduce the time and cost associated with traditional material development processes.

Sustainable Polymer Recycling and Circular Economy

With growing environmental concerns regarding plastic waste, future research should emphasize intelligent polymer recycling systems. Machine learning and computer vision techniques can be employed to automatically identify, classify, and sort different polymer types in recycling facilities. These technologies can improve recycling efficiency and contribute to sustainable material management within circular economy frameworks.

Federated Learning for Distributed Polymer Data

Many organizations possess valuable polymer datasets but face challenges in sharing data due to privacy and intellectual property concerns. Federated learning offers a promising solution by enabling collaborative model training across multiple institutions without transferring raw data. Future studies can explore federated learning frameworks for polymer informatics to improve model robustness while preserving data security.

Integration with Industry 5.0 Technologies

The emergence of Industry 5.0 emphasizes human-centric, sustainable, and resilient manufacturing systems. Future polymer analysis platforms can leverage artificial intelligence, collaborative robotics, edge computing, and smart sensors to create adaptive production environments. Such systems will support intelligent decision-making, enhance product quality, and promote sustainable manufacturing practices.

Future advancements in polymer detection and computer-based analysis are expected to be driven by the convergence of artificial intelligence, explainable machine learning, digital twins, multimodal data analytics, and smart manufacturing technologies. These developments will enable more accurate

material characterization, accelerated polymer discovery, sustainable recycling, and intelligent production systems, ultimately transforming the field of polymer informatics and advanced material engineering.

CONCLUSION

Traditional polymer detection and characterization techniques, including Fourier Transform Infrared Spectroscopy (FTIR), Raman Spectroscopy, Scanning Electron Microscopy (SEM), Transmission Electron Microscopy (TEM), Nuclear Magnetic Resonance (NMR), Differential Scanning Calorimetry (DSC), and Thermogravimetric Analysis (TGA), remain fundamental tools for understanding polymer structure, composition, and performance. These techniques provide detailed information about chemical bonding, molecular arrangement, surface morphology, thermal stability, and mechanical properties, making them indispensable in research laboratories and industrial quality control processes. Their high accuracy and reliability have enabled significant advancements in polymer science and engineering over the past several decades.

Despite their effectiveness, conventional characterization methods often involve complex experimental procedures, expensive instrumentation, and extensive manual interpretation of results. The growing volume and complexity of polymer-related data have created a demand for more efficient and automated analytical approaches. In response, recent developments in machine learning, deep learning, computer vision, and explainable artificial intelligence (XAI) have transformed polymer analysis by enabling automated classification, property prediction, defect detection, and material optimization. Advanced algorithms can analyze spectroscopic signals, microscopic images, and thermal datasets with high accuracy while reducing human intervention and processing time.

Deep learning models, particularly convolutional neural networks (CNNs), have demonstrated remarkable success in image-based polymer identification and defect recognition. Similarly, machine learning techniques such as Random Forests, Support Vector Machines, and Artificial Neural Networks are increasingly used for predicting polymer properties and processing outcomes. Explainable AI further enhances trust and transparency by providing interpretable insights into model decisions.

Future intelligent material informatics systems are expected to integrate experimental characterization techniques with AI-driven prediction, optimization, and interpretation frameworks. Such systems will facilitate accelerated polymer discovery, real-time quality control, sustainable recycling strategies, and the development of next-generation materials. The convergence of advanced characterization technologies and artificial intelligence promises to revolutionize polymer research, manufacturing, and environmental sustainability.

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