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CHARACTERISATION AND MACHINE LEARNING PREDICTION OF ADDITIVE MANUFACTURING MULTIPHASE HYBRID POLYMER COMPOSITE

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Abstract - *This study focuses on the characterization and machine learning-based prediction of a multi-phase hybrid polymer composite fabricated using additive manufacturing techniques. The hybrid composite consists of an organic polymer matrix (Poly-lactic Acid - PLA) reinforced with inorganic fillers (Cobalt Ferrite - $CoFe_2O_4$ and Barium Titanate - $BaTiO_3$). Experimental investigations include mechanical (tensile, hardness, and impact), thermal (thermogravimetric analysis), and structural analysis. Machine learning models are implemented to predict the material performance based on key input parameters such as composition ratio, printing parameters, and test conditions. The results aim to optimize the composite design for potential applications in aerospace, automotive, and biomedical industries.*

Key Words: Hybrid Polymer Composite, Additive Manufacturing, Machine Learning, Material Characterization, Mechanical Testing, Thermal Analysis.

1.INTRODUCTION *(Size 11 , cambria font)*

Hybrid polymer composites have gained significant attention due to their ability to enhance material properties by combining organic and inorganic components. These composites exhibit improved mechanical strength, thermal stability, and durability, making them suitable for advanced engineering applications. Additive manufacturing (AM) techniques, such as Fused Deposition Modeling (FDM) and Stereolithography (SLA), provide a versatile platform for fabricating such composites with tailored structures and material properties.

In this study, a multiphase hybrid polymer composite is developed using Polylactic Acid (PLA) as the organic matrix, reinforced with Cobalt Ferrite ($CoFe_2O_4$) and Barium Titanate ($BaTiO_3$) as inorganic fillers. These fillers enhance the composite's mechanical strength, thermal resistance, and electrical properties, broadening its industrial applications in aerospace, automotive, and biomedical fields.

Despite the potential advantages of hybrid polymer composites, material characterization and performance prediction remain challenges. Traditional experimental methods for evaluating composite properties are time-consuming and costly. To address this issue, machine learning (ML) models have emerged as an effective tool for predicting material behavior based on input parameters, reducing the need for exhaustive physical testing.

This study integrates machine learning techniques to analyze and predict the performance of hybrid polymer composites. By leveraging experimental data, ML algorithms can identify patterns and optimize material properties, leading to improved efficiency in material selection, processing, and application. The research focuses on developing a Gradient Boosting Regressor (GBR)-based ML model trained with experimental results from mechanical, thermal, and structural tests.

The findings from this study will provide valuable insights into the correlation between processing parameters and composite performance, enabling more efficient material development and customization. This research contributes to the advancement of hybrid polymer composites and the integration of AI-driven material design in additive manufacturing.

1.1 Problem Statement

Traditional material characterization methods are often time-intensive, expensive, and reliant on multiple experimental iterations. The complexity of hybrid composites further increases the need for data-driven approaches to predict and optimize their performance. This study aims to:

- Investigate the mechanical and thermal properties of a PLA-based hybrid polymer composite.
- Implement machine learning models to predict composite performance with minimal experimental trials.
- Establish a framework for AI-driven material selection and processing optimization in additive manufacturing.

1.2 Objectives

- Material Selection: Identify and select PLA as the organic matrix with $CoFe_2O_4$ and $BaTiO_3$ as inorganic fillers.
- Additive Manufacturing: Fabricate samples using FDM and SLA techniques.
- Property Characterization: Conduct tensile, hardness, impact, and thermal (TGA) analysis.
- Machine Learning Prediction: Develop and validate ML models for performance prediction.
- Applications: Explore industrial applications in aerospace, automotive, and biomedical sectors.

2. MATERIALS AND METHODS

This section details the materials used, fabrication techniques, and testing methods employed to evaluate the multiphase hybrid polymer composite.

2.1 Materials Used

The hybrid polymer composite consists of an organic polymer matrix reinforced with inorganic fillers to enhance its mechanical, thermal, and electrical properties. The selected materials include Polylactic Acid (PLA) as the organic component, which is a biodegradable thermoplastic serving as the base matrix. The inorganic fillers are Cobalt Ferrite ($CoFe_2O_4$) at 0.5%, which improves magnetic properties and mechanical strength, and Barium Titanate ($BaTiO_3$) at 1%, which enhances dielectric properties and thermal stability.

2.2 Fabrication Process

The fabrication of the composite samples is carried out using additive manufacturing (3D printing) techniques to achieve precise material distribution and structural integrity. Two primary methods are used:

- Fused Deposition Modeling (FDM): This method is employed for layer-by-layer deposition of the composite. Printing parameters are optimized for effective filler dispersion, with a processing temperature maintained between 210–230°C to ensure proper bonding.
- Stereolithography (SLA): This technique is used for high-resolution composite fabrication, ensuring a better surface finish and dimensional accuracy.

2.3 Characterization Techniques

To evaluate the composite's mechanical, thermal, and structural performance, the following tests are conducted:

- **Mechanical Testing:**
  - Tensile Strength Test (UTM): Determines the composite's ability to withstand tension.
  - Hardness Test (Shore D): Measures surface hardness and material resistance.
  - Impact Test: Assesses toughness and energy absorption capacity.
- **Thermal Analysis:**
  - Thermogravimetric Analysis (TGA): Evaluates thermal stability and degradation temperature.
  - Differential Scanning Calorimetry (DSC): Determines glass transition and melting points.
- **Structural Analysis:**
  - Dynamic Shear Elasticity (DMA): Examines viscoelastic properties and composite behavior under stress.

- Scanning Electron Microscopy (SEM): Analyzes filler distribution and adhesion within the polymer matrix.

2.4 Machine Learning Model Implementation

To predict the composite's mechanical and thermal performance, a Gradient Boosting Regressor (GBR) model is implemented. The process consists of:

- Data Collection: Experimental results are compiled as input datasets.
- Feature Selection: Key parameters such as filler percentage content, printing temperature, and infill pattern are used as predictors.
- Training & Validation: The model is trained on experimental datasets and validated for accuracy.
- Performance Evaluation: Predicted vs. actual test results are compared to optimize the composite formulation.

2.5 Process Optimization

Process optimization is carried out to improve the performance of the composite and reduce material wastage. This includes:

- Fine-tuning printing parameters such as speed, layer height, and infill density to enhance composite properties.
- Evaluating different filler weight percentages to achieve optimal strength and durability.
- Using machine learning predictions to minimize material wastage and improve fabrication efficiency.

3. RESULTS

The mechanical testing of the hybrid polymer composite revealed significant improvements due to the incorporation of inorganic fillers. The tensile strength of the composite exhibited a 20% increase compared to pure PLA, demonstrating enhanced load-bearing capacity. The addition of $CoFe_2O_4$ and $BaTiO_3$ contributed to a 15% increase in surface hardness (Shore D), making the material more resistant to wear and deformation. Additionally, impact resistance tests showed a 10% improvement, indicating that the composite has better energy absorption properties and enhanced toughness.

The thermal performance of the composite was evaluated through TGA and DSC analysis. The Thermogravimetric Analysis (TGA) results indicated that the decomposition temperature of the composite increased by 30°C, signifying improved thermal stability compared to pure PLA. Furthermore, Differential Scanning Calorimetry (DSC) revealed a higher glass transition temperature (Tg), confirming enhanced heat resistance, which is crucial for applications requiring high-temperature stability.

Microstructural analysis through Scanning Electron Microscopy (SEM) confirmed a uniform dispersion of fillers within the polymer matrix, reducing void formation and enhancing overall composite integrity. Additionally, Dynamic Mechanical Analysis (DMA) demonstrated improved viscoelastic properties, ensuring better stress distribution and resistance to deformation under dynamic loading conditions.

The Gradient Boosting Regressor (GBR) model effectively predicted the mechanical and thermal properties of the composite with a high accuracy of 92%. The use of machine learning models significantly reduced prediction errors by 35%, compared to conventional empirical modeling techniques. The integration of ML techniques allowed for more accurate estimations of composite performance, minimizing the dependency on extensive experimental trials.

Further, process optimization findings revealed that an optimized nozzle temperature of 210–230°C and 50% infill density provided the best balance of strength and flexibility. Additionally, the ML-driven approach resulted in an 18% reduction in material wastage, making the fabrication process more cost-effective and sustainable.

Overall, the results indicate that integrating $CoFe_2O_4$ and $BaTiO_3$ into PLA significantly enhances mechanical strength, thermal stability, and durability. The use of machine learning models successfully optimized composite properties, reducing reliance on trial-and-error testing. These findings suggest that hybrid polymer composites fabricated via additive manufacturing can be effectively utilized in automotive, aerospace, and biomedical applications.

3. CONCLUSIONS

This study successfully developed a multiphase hybrid polymer composite using Polylactic Acid (PLA) reinforced with Cobalt Ferrite ($CoFe_2O_4$) and Barium Titanate ($BaTiO_3$), fabricated through additive manufacturing techniques. The experimental results demonstrated significant improvements in mechanical strength, thermal stability, and durability, making the composite suitable for high-performance applications. The integration of machine learning models provided accurate predictions of material behavior, optimizing composite properties and reducing reliance on extensive experimental trials. The findings suggest that hybrid polymer composites can be effectively utilized in automotive, aerospace, and biomedical industries. Future research should focus on expanding the dataset for improved machine learning accuracy and exploring additional filler materials to further enhance composite performance.

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