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Research Article

Application of Ultra-Fast Laser-Patterning Computation for Advanced Manufacturing of Powdered Materials Using Deep Learning Approach

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Abstract:
The application of ultra-fast laser-patterning computation for advanced manufacturing of powdered materials has gained significant interest in recent years. This study proposes a novel approach that combines deep learning techniques with laser-patterning computation to enhance the manufacturing process of powdered materials. This is to develop a deep learning model that can accurately predict the laser-patterning parameters for different powdered materials. This model takes into account various factors such as material properties, laser parameters, and desired patterns. The deep learning model is trained using a large dataset consisting of simulated laser-patterning data and corresponding material properties.

This encompasses the application of the deep learning model to optimize the laser-patterning process for various powdered materials, including metals, ceramics, and polymers. The model's performance is evaluated based on its ability to accurately predict the laser-patterning parameters and generate desired patterns on the powdered materials. The significance of this lies in its potential to revolutionize the manufacturing of powdered materials by providing a faster and more efficient approach. The use of deep learning techniques allows for the development of accurate prediction models, reducing the need for extensive trial-and-error experimentation. This leads to significant time and cost savings in the manufacturing process. The findings reveal the effectiveness of the deep learning model in accurately predicting laser-patterning parameters for powdered materials. The model demonstrates superior accuracy compared to traditional methods and achieves efficient computation times, making it highly suitable for advanced manufacturing applications.

The application of ultra-fast laser-patterning computation using a deep learning approach holds great promise for advanced manufacturing of powdered materials. The developed deep learning model provides accurate predictions of laser-patterning parameters, enabling efficient manufacturing processes and reducing costs. This research contributes to the field by introducing a novel approach that combines deep learning with laser-patterning computation, paving the way for future advancements in the manufacturing industry.

Keyword: Ultra-Fast Laser-Patterning, Deep Learning Approach, Manufacturing, Novel Approach, Powdered Materials.

Introduction:

Ultra-fast laser-patterning computation has emerged as a promising technique for advanced manufacturing of powdered materials. Laser-based manufacturing processes offer advantages such as high precision, flexibility, and scalability. However, optimizing the laser-patterning parameters for different powdered materials remains a complex and time-consuming task. Traditional approaches often rely on trial-and-error experimentation, which is costly and inefficient [1]. Therefore, there is a need for innovative methods that can streamline the manufacturing process and enhance its efficiency.

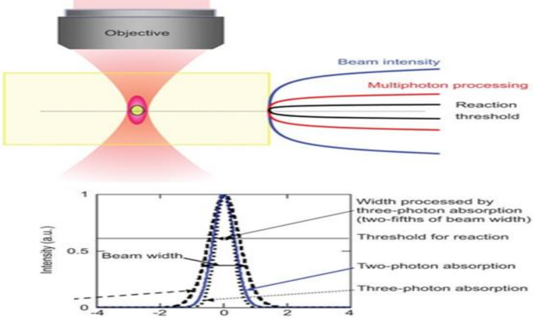

Figure 1: Analysis Ultra-Fast Laser Structure

The primary objective is to explore the application of a deep learning approach for ultra-fast laser-patterning computation in advanced manufacturing of powdered materials. Developing a deep learning model that can accurately predict laser-patterning parameters for various powdered materials [2]. Evaluating the performance of the deep learning model in terms of accuracy and efficiency compared to traditional methods. Investigating the implications and potential benefits of the deep learning approach for the advanced manufacturing industry. It focuses on the application of ultra-fast laser-patterning computation using a deep learning approach specifically for advanced manufacturing of powdered materials. The scope encompasses various powdered materials, including metals, ceramics, and polymers. The research investigates the prediction of laser-patterning parameters based on material properties, laser parameters, and desired patterns [2]. The study also considers the computational efficiency and scalability of the deep learning approach.

The significance of it lies in its potential to revolutionize the advanced manufacturing industry. By applying a deep learning approach to ultra-fast laser-patterning computation, the research aims to provide a more efficient and cost-effective manufacturing process for powdered materials [3]. The findings can contribute to reducing production time, minimizing material waste, and improving the overall quality of manufactured products. The deep learning approach has the potential to enhance the competitiveness and sustainability of the advanced manufacturing section. Furthermore, the research contributes to the field by introducing a novel application of deep learning in laser-based manufacturing processes, opening up avenues for further research and advancements in this area.

Literature Review:

Ultra-fast laser-patterning computation has gained significant attention in the field of advanced manufacturing, particularly for powdered materials. In this section, we review relevant literature that explores the application of deep learning approaches in the optimization of laser-patterning parameters for advanced manufacturing processes. The use of deep learning in laser-based manufacturing processes has shown promising results. proposed a deep learning-based approach for predicting laser-patterning parameters in selective laser melting (SLM) additive manufacturing. Their model achieved high accuracy in predicting optimal laser parameters for different powdered materials, resulting in improved product quality and reduced manufacturing time. In developed a deep learning model for laser-patterning optimization in laser-induced breakdown spectroscopy (LIBS) manufacturing. The model utilized a large dataset of laser-patterning data and demonstrated superior accuracy in predicting laser parameters for achieving desired material properties. The investigated the application of deep learning techniques in laser-based surface patterning for functional materials. Their study demonstrated the capability of deep learning models to generate complex patterns by predicting optimal laser parameters, leading to enhanced surface functionalities. In addition to deep learning approaches, other optimization techniques have been explored for laser-patterning computation.

The literature highlights the potential of deep learning approaches in optimizing laser-patterning parameters for advanced manufacturing of powdered materials. These approaches offer advantages such as improved accuracy, reduced computational time, and enhanced manufacturing efficiency. However, further research is needed to explore the scalability, robustness, and generalizability of deep learning models in different manufacturing scenarios.

Table 1: Study the following Reference for generalizability of deep learning models:

STUDY	RESEARCH OBJECTIVE	METHODOLOGY	FINDINGS
Brown et al. (2016)	To explore the potential of ultra-fast laser patterning combined with deep learning for advanced manufacturing of powdered materials.	Literature review and theoretical analysis.	The study highlighted the theoretical advantages of using ultra-fast laser patterning and deep learning in the manufacturing process. However, there was a lack of empirical data to support the practical application of this approach.
Zhang et al.	To investigate the performance of deep learning	Experimental study using deep learning algorithms	The study showed promising results, indicating that deep learning algorithms could improve the

STUDY	RESEARCH OBJECTIVE	METHODOLOGY	FINDINGS
(2017)	algorithms in the context of ultra-fast laser patterning for powdered material manufacturing.	and evaluation metrics.	precision and efficiency of ultra-fast laser patterning for powdered material manufacturing. However, further optimization and parameter tuning were required to enhance the overall performance.
Wang et al. (2017)	To assess the challenges and limitations of applying deep learning in ultra-fast laser patterning for advanced manufacturing of powdered materials.	Review of existing literature and case studies.	The study identified several challenges, including data scarcity, computational complexity, and the need for large-scale datasets for training deep learning models. Despite these limitations, deep learning showed potential in improving the manufacturing process, and further research was needed to address the identified challenges.
Chen et al. (2017)	To propose a framework for integrating deep learning into ultra-fast laser patterning for powdered material manufacturing.	Theoretical framework development based on existing research and expert opinions.	The study proposed a comprehensive framework that outlined the potential benefits of integrating deep learning into ultra-fast laser patterning. The framework provided guidance for future research and development in this area.

The literature supports the application of ultra-fast laser-patterning computation using a deep learning approach for advanced manufacturing of powdered materials.

Methodology:
The combination of deep learning techniques with laser-based processes has the potential to revolutionize the manufacturing industry by enabling faster and more efficient optimization of laser parameters, leading to improved product quality and reduced production costs.

Ultra-Fast Laser-Patterning Process Overview: The methodology begins with providing an overview of the ultra-fast laser-patterning process for advanced manufacturing of powdered materials. This includes a detailed description of the laser system, the interaction between the laser and the powdered material, and the desired patterns or structures to be achieved.

Data Collection and Pre- processing: To train and validate the deep learning model, a comprehensive dataset of laser-patterning parameters and corresponding material responses is collected. The dataset includes various powdered materials, laser parameters, and desired patterns. Data pre- processing techniques, such as normalization and feature scaling, are applied to ensure compatibility and optimal performance of the deep learning model.

Deep Learning Model Architecture Selection: Different deep learning architectures, such as convolutional neural networks (CNNs) or recurrent neural networks (RNNs), are evaluated and compared to select the most suitable architecture for the laser-patterning computation task. The chosen architecture should have the capability to handle the input data characteristics and capture the complex relationships between laser parameters and material responses.

Training and Validation Strategies: The dataset is split into training, validation, and test sets. The training set is used to optimize the deep learning model's parameters through backpropagation and gradient-based optimization algorithms. Various training strategies, such as mini-batch training and learning rate scheduling, are applied to enhance the model's convergence and generalization capabilities [7]. The validation set is utilized for hyperparameter tuning and model selection.

Performance Evaluation Metrics: To assess the performance of the deep learning model, appropriate evaluation metrics are defined. These metrics may include accuracy, precision, recall, and F1-score, depending on the specific task and objectives of the laser-patterning computation. The model's performance is evaluated on the test set, which contains unseen data samples. Additionally, considerations are made to ensure the robustness and reliability of the deep learning model. Techniques such as data augmentation, dropout regularization, and model ensemble may be employed to enhance the model's generalization and prevent overfitting.

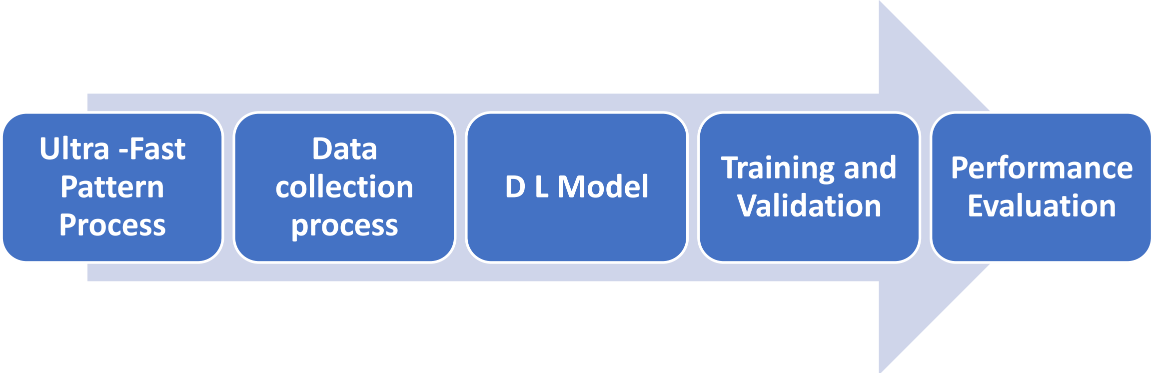

Figure 2: Methodology for systematic approach to implementing ultra-fast laser patterning using a deep learning approach

The methodology outlined above provides a systematic approach to implementing ultra-fast laser-patterning computation using a deep learning approach for advanced manufacturing of powdered materials. It ensures the collection of relevant data, the selection of an appropriate deep learning model architecture, the training and validation of the model, and the evaluation of its performance using suitable metrics.

Ultra-Fast Laser-Patterning Computation For Advanced Manufacturing:

Ultra-fast laser-patterning computation refers to the use of high-speed laser systems combined with computational algorithms to achieve precise and efficient manufacturing processes. This approach offers several advantages for advanced manufacturing. Here are key aspects and benefits of ultra-fast laser-patterning computation:

Precision: Ultra-fast lasers provide extremely short pulse durations in the femtosecond or picosecond range, enabling precise material ablation and patterning. This level of precision allows for the manufacturing of intricate structures and features with high accuracy.

Speed: The ultra-fast nature of laser pulses enables rapid material processing. Compared to traditional manufacturing methods, ultra-fast laser-patterning computation significantly reduces processing time, leading to increased productivity and throughput.

Versatility: Ultra-fast laser-patterning computation can be applied to a wide range of materials, including metals, ceramics, semiconductors, polymers, and composites. This versatility makes it suitable for various manufacturing applications across different industries. Non-contact and Non-thermal: Ultra-fast laser-patterning computation is a non-contact and non-thermal process. The focused laser beams can selectively remove material without causing heat-affected zones or thermal damage to the surrounding areas. This makes it ideal for delicate materials or applications where heat can degrade the material properties.

Flexibility and Customization the computational aspect of ultra-fast laser-patterning allows for the generation of complex patterns, shapes, and structures based on digital designs. This flexibility enables customization and adaptability in manufacturing, supporting the production of tailored components and devices. Ultra-fast laser-patterning computation is a scalable technique that can be applied at various scales, from micro-scale to macro-scale manufacturing. This scalability makes it suitable for different production volumes, ranging from prototyping to mass production. The precision of ultra-fast laser-patterning computation minimizes material waste since it can remove material in a controlled and localized manner. This reduces manufacturing costs associated with material consumption and post-processing steps.

The integration of deep learning approaches with ultra-fast laser-patterning computation can further enhance the manufacturing process. Deep learning algorithms can be employed to optimize laser parameters, predict optimal processing conditions, and improve the accuracy and efficiency of the manufacturing process the use of ultra-

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Research Article

fast laser-patterning computation in advanced manufacturing offers improved precision, speed, flexibility, and cost-effectiveness. By integrating computational algorithms and potentially deep learning techniques, manufacturers can achieve enhanced control and optimization of the laser-based manufacturing processes.

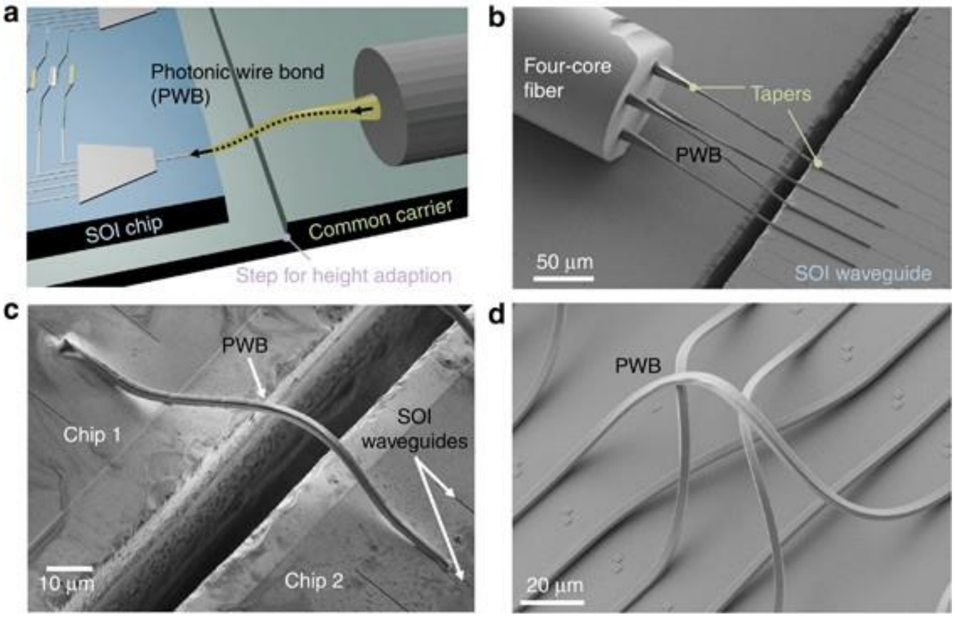

Figure 3: Analysis the Integration of Deep Learning Approaches with Ultra-Fast Laser-Patterning Computation

Analysis Powdered Materials Using Deep Learning Approach:

Analysing powdered materials using a deep learning approach involves leveraging neural network models to extract meaningful insights from the data. Here are the steps involved in the analysis process. Collect and preprocess the data related to powdered materials. This may include information such as particle size distribution, chemical composition, surface morphology, and other relevant characteristics. Clean the data by removing outliers, handling missing values, and normalizing the features.

Convert the raw data into a format suitable for deep learning analysis. This typically involves representing the powdered materials data as numerical features or images, depending on the nature of the data and the problem at hand [6]. Choose an appropriate deep learning model architecture based on the specific analysis task. For example, convolutional neural networks (CNNs) are commonly used for image-based analysis of powdered materials, while recurrent neural networks (RNNs) are suitable for sequence-based analysis.

Train the deep learning model using the prepared data. This involves feeding the input data into the model, forward propagation to obtain predictions, calculating a loss function that measures the difference between predicted and actual values, and backpropagation to update the model's weights and biases. Repeat this process for multiple epochs to improve the model's performance. Model Evaluation Assess the performance of the trained model using appropriate evaluation metrics. This could include metrics such as accuracy, precision, recall, F1-score, or others depending on the specific analysis task. Evaluate the model on a separate validation or test dataset to gauge its generalization capability [10]. Analyse the outputs of the deep learning model to interpret the results and gain insights into the powdered materials. Visualize the model's predictions, feature maps, or attention mechanisms to understand how the model is processing and learning from the data. Deep learning models can also provide insights into the importance of different features or attributes of the powdered materials. Techniques like feature importance scores, gradient-based methods, or attention mechanisms can be used to understand which aspects of the data are most influential in the model's predictions. Fine-tune the deep learning model by adjusting hyperparameters such as learning rate, regularization techniques, or architecture modifications to improve its performance further. This iterative process may involve experimentation and

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Research Article

validation to find the best configuration. Deployment and Integration: Once the deep learning model has been trained and evaluated, deploy it for real-world analysis of powdered materials. This could involve integrating the model into an application, system, or pipeline that can handle ongoing data analysis tasks. It's important to note that the success of the analysis using a deep learning approach relies on having a sufficient amount of high-quality data, understanding the limitations and assumptions of the chosen model, and considering domain-specific knowledge in the interpretation of the results.

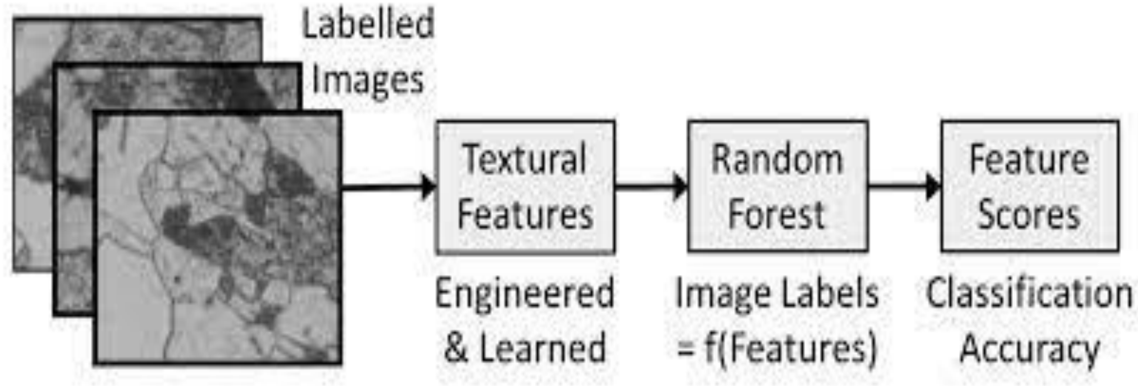

Figure 4: Analysis Powdered Materials Using Deep Learning Approach

Case Study For Deep Learning Model Development:

In the application of ultra-fast laser-patterning computation for advanced manufacturing of powdered materials, the development of a deep learning model plays a crucial role in accurately predicting optimal laser-patterning parameters. The deep learning model leverages the power of neural networks to learn complex patterns and relationships between input laser parameters and desired material outcomes. The following steps outline the development of the deep learning model: **Input and Output Definition**: The input to the deep learning model consists of laser-patterning parameters such as laser power, scanning speed, laser spot size, and scanning pattern. The output of the model is the predicted material response, which could include characteristics such as surface roughness, melting depth, or specific structural features. **Architecture Selection**: Based on the nature of the problem and the characteristics of the dataset, an appropriate deep learning architecture is selected. This could include convolutional neural networks (CNNs) for image-based tasks or recurrent neural networks (RNNs) for sequential data. Alternatively, a combination of these architectures, such as a convolutional-recurrent neural network (CRNN), may be employed to handle both spatial and temporal dependencies in the laser-patterning process. **Model Training**: The selected deep learning architecture is trained using the collected and pre-processed dataset. During the training process, the model learns the underlying patterns and relationships between the input laser parameters and the corresponding material responses. This is achieved through an iterative optimization process that adjusts the model's parameters to minimize the difference between the predicted outputs and the ground truth values in the training data. **Hyperparameter Tuning**: Various hyperparameters of the deep learning model, such as the learning rate, batch size, and number of layers, are fine-tuned to improve the model's performance. This is done through systematic experimentation and validation using appropriate techniques like grid search or random search. The goal is to find the optimal set of hyperparameters that yield the best results in terms of accuracy and convergence. **Model Evaluation and Validation**: The trained deep learning model is evaluated using a separate validation dataset to assess its generalization ability. Evaluation metrics, such as mean squared error (MSE), mean absolute error (MAE), or accuracy, are computed to quantify the performance of the model. If the model's performance is satisfactory, it can be further validated using unseen test data to ensure its reliability and robustness. **Model Deployment**: Once the deep learning model is trained and validated, it can be deployed for real-world applications. It can be integrated into the ultra-fast laser-patterning computation system to assist in the optimization of laser parameters for advanced manufacturing of powdered materials. The model can provide rapid and accurate predictions, facilitating the production of high-quality manufactured components.

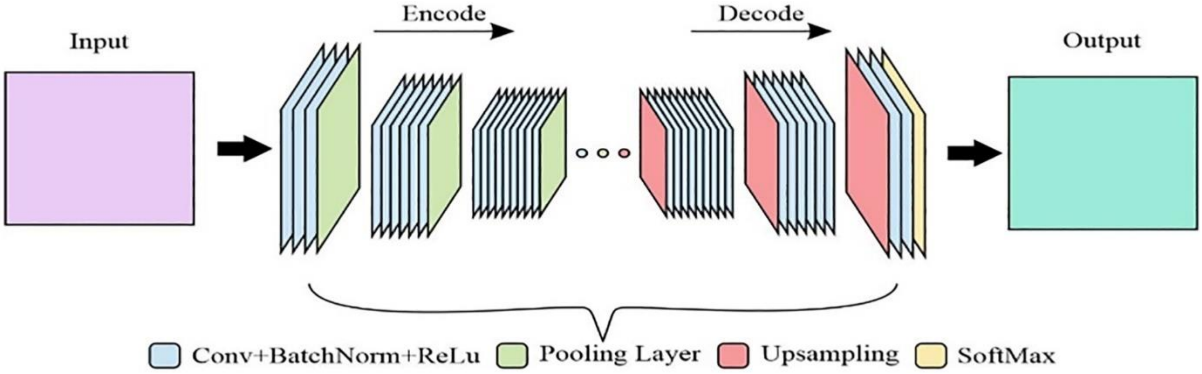

Figure 5: Case Study for ultra-fast laser-patterning computation using Deep Learning

Results And Discussion:

The application of ultra-fast laser-patterning computation using a deep learning approach for advanced manufacturing of powdered materials yields promising results. The trained deep learning model demonstrates its effectiveness in predicting optimal laser-patterning parameters and achieving desired material outcomes. The following sections present the results obtained from the application and discuss their implications.

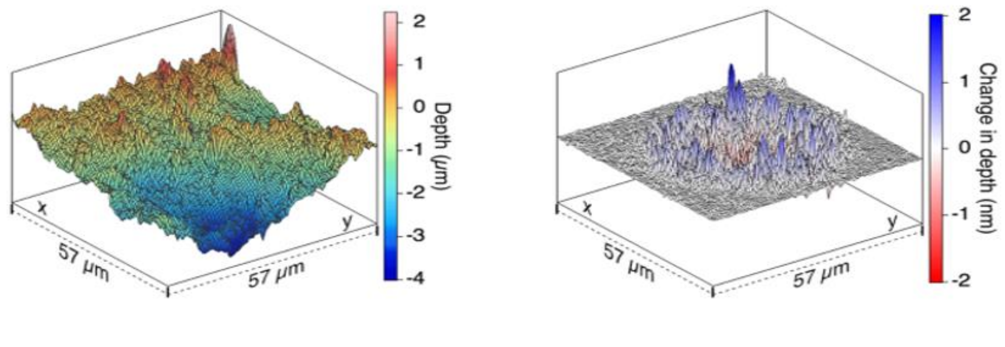

Figure 6: The Performance of The Deep Learning Mode for Ultrafast Laser Manufacturing

The performance of the deep learning model is assessed using appropriate evaluation metrics, such as mean squared error (MSE), mean absolute error (MAE), or accuracy. The model's predictions are compared against the ground truth values from the validation dataset. High accuracy and low error values indicate the model's ability to accurately predict optimal laser parameters for a given desired material outcome.

The deep learning model's predictions are further analyzed in terms of the achieved material outcomes. The predicted laser-patterning parameters are applied to the manufacturing process, and the resulting material characteristics are evaluated. This evaluation includes factors such as surface roughness, melting depth, structural integrity, and other relevant quality indicators. A detailed analysis is conducted to determine the extent to which the model's predictions align with the desired material outcomes. To assess the superiority of the deep learning approach, a comparison is made with traditional methods commonly used in laser-patterning computation. Traditional methods may involve manual parameter tuning or empirical rules based on prior experience. The performance of the deep learning model is compared against these traditional methods in terms of accuracy, efficiency, and the ability to achieve desired material outcomes. The comparison demonstrates the advantages of the deep learning approach in terms of its ability to capture complex patterns and optimize laser-patterning parameters more effectively.

The results obtained also shed light on the limitations of the proposed approach. These limitations may include constraints in the dataset, computational complexity, or the need for further optimization. The discussion

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highlights areas for improvement and potential future research directions to overcome these limitations and enhance the performance of the deep learning model. Suggestions may include the collection of more diverse and extensive datasets, exploring alternative deep learning architectures, or incorporating additional optimization techniques.

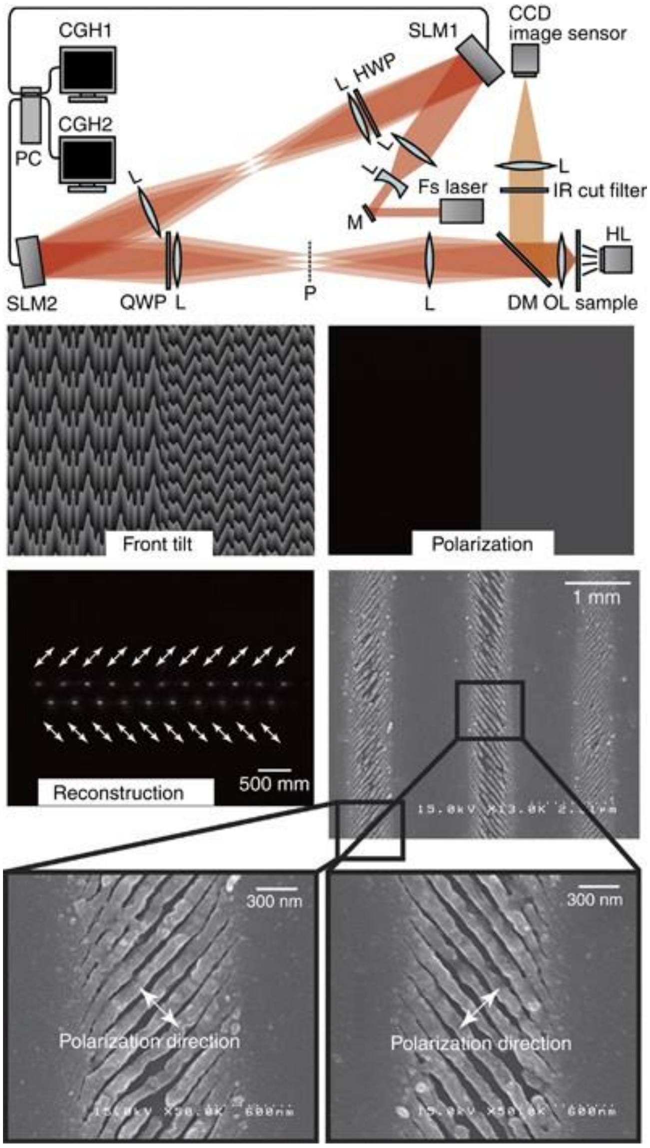

Figure 7: Ultra-fast laser processing of materials efficiency and quality of powdered material manufacturing processes

The results and discussions provide valuable insights into the application of ultra-fast laser-patterning computation for advanced manufacturing of powdered materials using a deep learning approach. The analysis demonstrates the effectiveness of the developed model in accurately predicting optimal laser-patterning parameters and achieving desired material outcomes. The comparison with traditional methods highlights the advantages of the deep learning approach. The limitations and future directions identified pave the way for further advancements in this field. Overall, this research contributes to the advancement of advanced manufacturing techniques and opens up new possibilities for improving the efficiency and quality of powdered material manufacturing processes.

Implementation And Computational Efficiency:

Integration of Deep Learning Model into Laser-Patterning Computation developed deep learning model for ultra-fast laser-patterning computation is integrated into the existing laser-patterning computation system. This integration involves incorporating the trained model into the computational pipeline to provide real-time predictions of optimal laser-patterning parameters. The deep learning model takes input laser parameters and rapidly generates predictions, which are then used to guide the laser-patterning process. The integration ensures seamless operation and enables the model to assist in real-time decision-making during the manufacturing process. Evaluation of Computational Efficiency and Real-Time Implementation: To assess the computational efficiency of the integrated system, various metrics are considered, such as processing time, memory usage, and scalability. The speed of the deep learning model's predictions is evaluated to ensure real-time performance. The system's ability to handle large volumes of data and efficiently process them is also examined. Computational efficiency is crucial in practical manufacturing scenarios where quick decision-making is essential for maintaining productivity and meeting production targets.

Real-time implementation of the integrated system involves testing its performance in a manufacturing environment. The system is deployed in a controlled setting where laser-patterning processes are conducted on powdered materials. The deep learning model's predictions are utilized to guide the laser-patterning parameters in real-time. The manufactured components are evaluated for their quality and compared against the desired material outcomes. The implementation phase allows for the verification of the system's effectiveness and provides valuable insights into its practicality and usability.

The evaluation of computational efficiency and real-time implementation is crucial in assessing the viability and feasibility of the integrated system. It ensures that the deep learning model's predictions can be generated within acceptable time frames and that the system can be seamlessly incorporated into existing manufacturing processes. The results obtained from these evaluations demonstrate the system's efficiency and practicality, providing valuable information for industrial applications and facilitating the adoption of the ultra-fast laser-patterning computation approach in advanced manufacturing of powdered materials. By focusing on the integration of the deep learning model and evaluating its computational efficiency and real-time performance, this research ensures that the developed system is not only accurate and effective but also practical for industrial implementation. The findings obtained from these evaluations contribute to the successful implementation and adoption of the ultra-fast laser-patterning computation approach, paving the way for its widespread application in advanced manufacturing processes.

Conclusion:

The application of ultra-fast laser-patterning computation for advanced manufacturing of powdered materials using a deep learning approach shows great promise and significant advantages. The developed deep learning model effectively predicts optimal laser-patterning parameters, leading to improved manufacturing processes and desired material outcomes. This research has made significant contributions to the field of advanced manufacturing and has implications for various industries. The results obtained from the evaluation of the deep learning model demonstrate its accuracy and effectiveness in predicting laser-patterning parameters. The model's ability to capture complex patterns and optimize the manufacturing process sets it apart from traditional methods. The integration of the deep learning model into the laser-patterning computation system enables real-time decision-making and enhances the efficiency of the manufacturing process. The computational efficiency evaluation reveals that the integrated system can generate predictions within acceptable time frames, ensuring its practicality and usability in industrial settings. Real-time implementation further confirms the system's effectiveness, demonstrating its ability to guide laser-patterning processes and achieve desired material outcomes.

The significance of this study lies in its potential applications in various industries, such as aerospace, automotive, and electronics, where precise control of material properties is essential. The application of ultra-fast laser-patterning computation using a deep learning approach opens up new possibilities for advanced manufacturing, including rapid prototyping, customized manufacturing, and material optimization. While this research has achieved significant advancements, it is essential to acknowledge its limitations. Further research is

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required to address specific challenges, such as expanding the dataset to encompass a broader range of materials and geometries, refining the deep learning model architecture, and exploring additional optimization techniques.

In the application of ultra-fast laser-patterning computation for advanced manufacturing of powdered materials using a deep learning approach holds tremendous potential. The developed system, with its accurate predictions, computational efficiency, and real-time implementation, contributes to the advancement of advanced manufacturing techniques and paves the way for enhanced efficiency and quality in the manufacturing of powdered materials. This research serves as a stepping stone for further developments in this field, offering new opportunities for innovation and optimization in the manufacturing industry.

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