Predicting Keyhole Pore Formation in Laser Powder Bed Fusion Using Deep Learning Models

Objective:

The objective of this project is to predict the formation of a pore in the keyholes of the Laser Powder Bed Fusion (LPBF) Additive Manufacturing process. The prediction aims to occur approximately 0.5 µs earlier than the pore formation. This advancement seeks to improve the overall quality and reliability of the LPBF process.

Methodology:

To achieve the desired objective of predicting the formation of a pore approximately 0.5 µs earlier in the keyholes of the Laser Powder Bed Fusion (LPBF) Additive Manufacturing process, numerous simulation images need to be collected to train a deep-learning model. For these simulations, two alloys were chosen: Al-6061 alloy and Ti-6Al-4V alloy. These materials were selected due to their prevalent use in additive manufacturing and their distinct thermal and mechanical properties, which provide a comprehensive dataset for training the model.

Once the simulation images are gathered, the initial aim is to use a Convolutional Neural Network (CNN) architecture for training. The CNN will be evaluated for its accuracy in predicting pore formation and the computational timing required for such predictions. Accuracy and timing are crucial metrics, as they will determine the model's feasibility for real-time application in the LPBF process.

For improved accuracy and computational efficiency, a Physics-Informed Neural Network (PINN) will be employed. The PINN will incorporate a physics-based loss function, leveraging the underlying physical principles of the LPBF process. This approach is expected to enhance the model's predictive capabilities by integrating domain-specific knowledge into the learning process.

The procedure can be divided into two parts:

1. Running Simulations of the LBPF Model in Ansys Fluent
2. Training CNN for prediction of pore formation in the keyhole

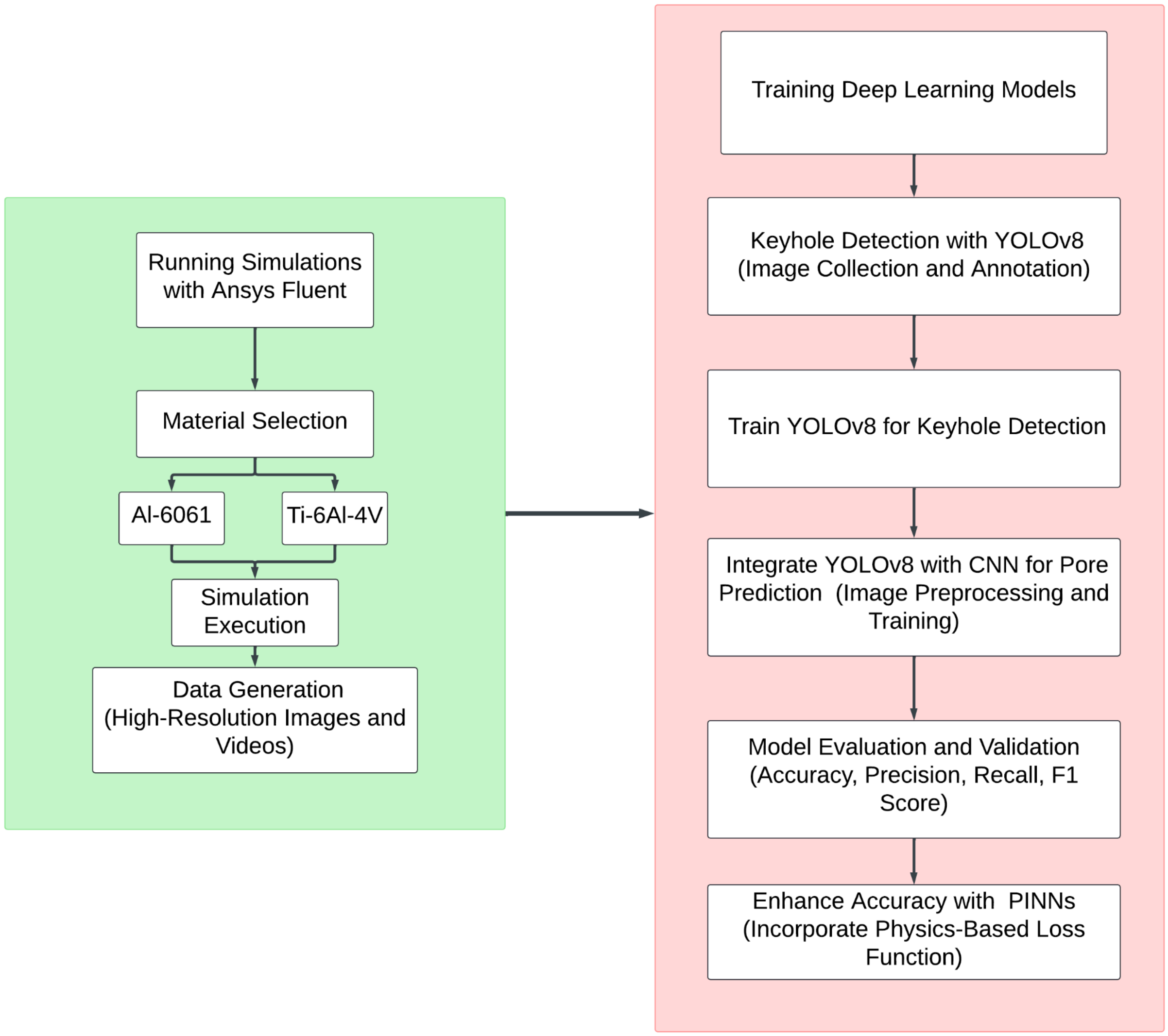

Figure 1: Workflow for Predicting Keyhole Pore Formation in LPBF Using Deep Learning Models

Part - I - Running Simulations of the LBPF Model in Ansys Fluent

The Laser Powder Bed Fusion (LPBF) simulation of Al-6061 alloy was successfully conducted using Ansys Fluent software. The material properties used in the simulation for Al-6061 are provided in Table 1. These properties include essential parameters such as solid density, liquid density, solidus and liquidus temperatures, specific heat capacities, thermal conductivities, latent heat of fusion, dynamic viscosity, thermal expansion coefficient, surface tension, and the Marangoni coefficient.

Custom User Defined Functions (UDF) were utilized for running the simulation. These UDFs were specifically developed to handle the complex interactions between the laser and the powder material, accounting for phase changes, thermal gradients, and fluid flow within the melt pool. The simulation aimed to replicate the real-world conditions of the LPBF process as closely as possible.

The simulation was successful, producing high-resolution images that clearly show the formation and evolution of keyholes and pores in the Al-6061 alloy. These images are shown in Figure 2, highlighting critical stages in the process. Additionally, the full simulation can be viewed in the accompanying video, which provides a dynamic visualization of the entire process, including temperature distribution and melt pool dynamics.

For the next step, the Ti-6Al-4V alloy was used. The properties of Ti-6Al-4V, which include its higher melting point and different thermal conductivity compared to Al-6061, are also listed in Table 1. These differences necessitate adjustments in the simulation parameters to accurately capture the behavior of Ti-6Al-4V under laser exposure.

During the simulation of Ti-6Al-4V, an issue arose with the UDF files. This issue affected the accuracy of the temperature distribution and melt pool formation, leading to discrepancies in the expected results. The troubleshooting of this issue is currently underway. Ensuring the correctness of the UDF is critical for obtaining reliable simulation results for Ti-6Al-4V.

This part of the procedure is vital for collecting accurate and diverse datasets that will be used to train the deep-learning model. The successful completion of simulations for both Al-6061 and Ti-6Al-4V will provide a robust foundation for the subsequent steps in the research.

Table 1: Summary of the material property

Property	**Ti-6Al-4V**	**Al - 6061**
Solid density (kg/m^3)	4420	2765-0.201T
Liquid Density (kg/m^3)	3920	2670-0.28T
Solidus Temperature (K)	1877	873
Liquidus Temperature (K)	1933	915

Solid Specific Heat Capacity ($J.kg^{-1}K^{-1}$)	452.72+0.1734T	0.7067+0.0006T- $(1 \times 10^{-7})T^2$
Liquid Specific Heat Capacity ($J.kg^{-1}K^{-1}$)	830	1170
Solid Thermal Conductivity ($W.m^{-1}K^{-1}$)	1.3097+0.0136T	90
Liquid Thermal Conductivity ($W.m^{-1}K^{-1}$)	33.4	66.5
Latent Heat of Fusion ($kJ.kg^{-1}K^{-1}$)	286	380
Dynamic Viscosity (Pa.s)	2.66×10^{-3}	1.00×10^{-3}
Thermal Expansion (1/K)	80×10^{-5}	
Surface Tension ($N.m^{-1}$)	1.8	1.8
Marangoni Coefficient ($N.m^{-1}K^{-1}$)	-2.6×10^{-4}	0
Processing parameters for simulations		
Ti6Al4V		
Beam radius	0.000025	0.0000044
Absorption, A	0.27	
Power, P (W)	170	416
Scanning speed, v (m/s)	0.5	0.6

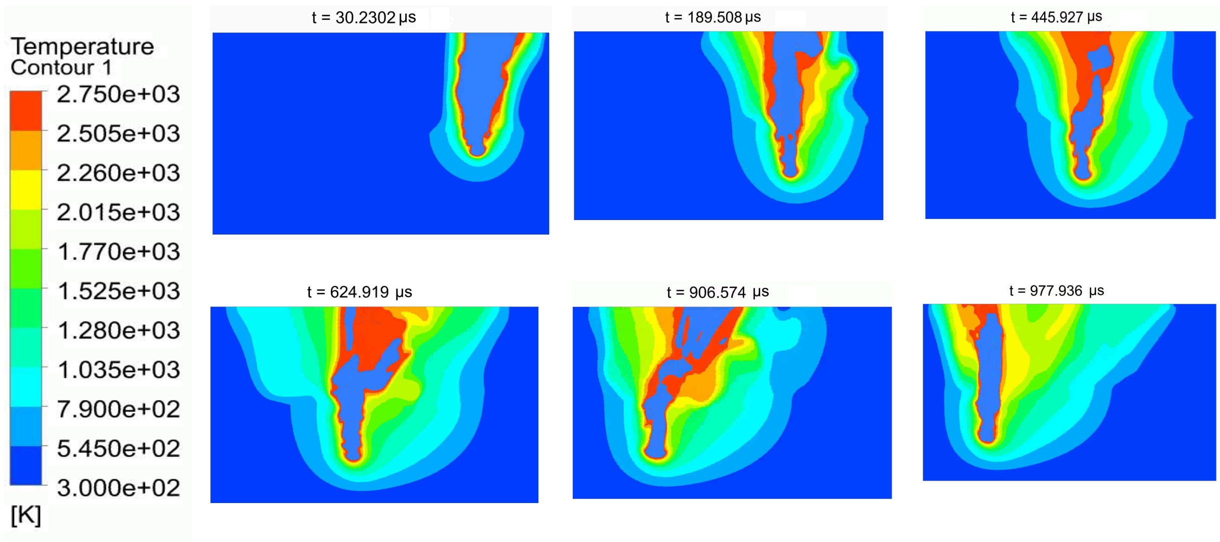

Figure 2: Pores formation within the molten pool at different timesteps

Part - II - Training CNN for prediction of pore formation in the keyhole

To achieve the final objective of predicting pore formation in the keyholes of the Laser Powder Bed Fusion (LPBF) process, a deep learning model needs to be trained. The initial step in this training involves the detection of keyhole formation in the molten pool. Detecting keyholes accurately is crucial as they are precursors to pore formation and provide critical information about the conditions leading to defects.

Keyhole Detection using YOLOv8

For keyhole detection, a You Only Look Once (YOLOv8) model was employed. This model was chosen for its high speed and accuracy in object detection tasks. The images used for training the YOLOv8 model were collected from experimental LPBF processes conducted at Northwestern University. These images capture various stages of the LPBF process, highlighting the formation and evolution of keyholes.

The collected images underwent a rigorous annotation process to ensure they were training-ready for the YOLOv8 model. Annotation involved labeling keyholes in the images, which provided the model with the necessary data to learn and detect keyholes effectively. Once trained, the YOLOv8 model demonstrated the ability to detect keyholes with a confidence range of 40-60%. An example of a detected keyhole with 44%

confidence is shown in Figure 3. This level of confidence indicates the model's initial success in identifying keyholes, though there is room for improvement.

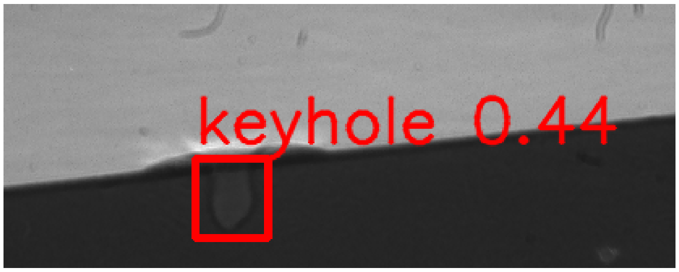

Figure 3: Image of a detected keyhole in the molten pool

Integration with CNN for Pore Formation Prediction

Following the successful detection of keyholes, the next step involves integrating the image data generated from the Ti-6Al-4V simulations with a Convolutional Neural Network (CNN). The CNN model will be trained to predict pore formation in the keyholes, leveraging the keyhole detection data as a foundational input. This integration is crucial as it allows the model to build on the detected keyholes to predict subsequent pore formation events.

The training process for the CNN will involve several stages:

1. **Data Preprocessing:** The simulation images from the Ti-6Al-4V alloy will be preprocessed to ensure compatibility with the CNN architecture. This includes normalization, augmentation, and splitting into training and validation sets.
2. **Model Training:** The CNN will be trained using the preprocessed images. The training will focus on optimizing the network's parameters to maximize its predictive accuracy. The model's performance will be evaluated based on metrics such as accuracy, precision, recall, and F1 score.
3. **Validation:** The trained CNN model will be validated using a separate set of images to assess its ability to generalize to new, unseen data. This step is critical to ensure the model's robustness and reliability in real-world applications.

Enhancing Accuracy with Physics-Informed Neural Networks (PINNs)

To further enhance the accuracy and timing of the predictions, a Physics-Informed Neural Network (PINN) will be utilized. The PINN incorporates a physics-based loss function, which leverages the underlying physical principles of the LPBF process. This integration of domain-specific knowledge allows the model to make more accurate and reliable predictions by adhering to the known physical laws governing keyhole and pore formation.

The PINN's physics-based loss function will be designed to minimize discrepancies between the predicted outcomes and the expected physical behavior of the LPBF process. This approach not only improves prediction accuracy but also ensures that the model's outputs are physically plausible and consistent with the observed phenomena.