Automated Classification of Martensitic and Pearlite Microstructures from Internet Data

A summary of the report is available at the end if needed.

Project Presentation

This project aims to develop a computer vision system capable of automatically classifying two types of metallic microstructures: martensite and pearlite. A key aspect of this project lies in the use of data extracted from the Internet, making the project not only innovative but also accessible, since the data is available to all. The quality and uniformity of these data play a crucial role, directly influencing the accuracy of the classification model. Through the experimentation of various convolutional neural network architectures, including the adaptation of the final layers of pretrained models to match our specific data, we aim to optimize the performance of our system.

State of the Art

Our project is part of the rapidly expanding field of computer vision, which applies machine learning and deep learning techniques to the interpretation of images captured by cameras. Artificial intelligence, encompassing machine learning, includes deep learning which involves teaching the system to automatically and hierarchically learn data characteristics. It employs deep artificial neural networks, inspired by the functioning of neurons in the human brain. These models are composed of multiple hidden layers, each capable of detecting features at various levels of abstraction.

Objective

The central goal of this project is to create a highly reliable and precise model for the classification of martensitic and pearlite microstructures, despite the challenges posed by using data extracted from the Internet. This data, often heterogeneous and of varying quality, can lead to overfitting risks and affect the model's generalizability. We are thus dedicated to optimizing the model's accuracy while refining the methods for cleaning and preparing the dataset. The objective is twofold: to enhance the model's robustness against data imperfections and, by extension, to advance the capabilities of computer vision in the field of metallurgy. This project aspires to demonstrate that with sophisticated data processing techniques, it is possible to extract accurate knowledge from diverse and imperfect sources, paving the way for innovative applications in research and industry.

Custom Dataset Preparation

Crafting our custom dataset required a methodical and rigorous approach, beginning with the collection of images from online sources through advanced scraping techniques. This initial process yielded a vast array of raw images, from which we had to identify and extract the relevant martensite and pearlite microstructures.

Key steps in the preparation included:

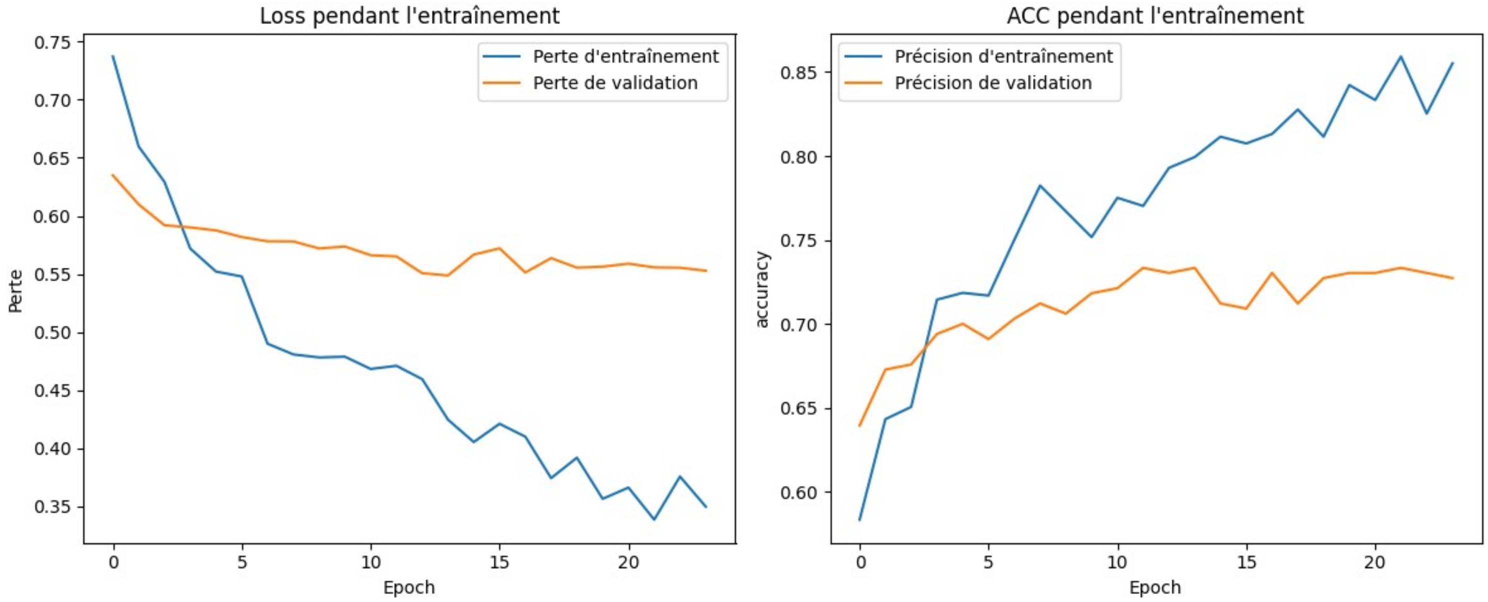
1. **Image Scraping:** Implementing scraping tools to gather raw images directly from online sources.
2. **Preprocessing:**
   - **Upscaling:** Enhancing the resolution of images for improved analysis and feature identification.
   - **Automated Cropping:** Employing a pretrained model on a smaller dataset to automatically detect and extract Regions of Interest (ROIs) from images. Although this model facilitated ROI identification, manual annotation of 200 images was necessary to refine our approach.
3. **Dataset Validation:** Developing a pre-classification model trained on a small set of manually verified high-quality images. This pre-model was used to filter the entire collection, discarding images with low classification confidence.
4. **Cleaning and Labeling:** Thorough cleaning and precise labeling of the remaining images created a consistent dataset, crucial for the effective training of our advanced classification models.
5. **Model Training:** With a cleaned and rigorously prepared dataset, the final step was training our classification model, aiming for optimal precision in distinguishing between martensite and pearlite microstructures.

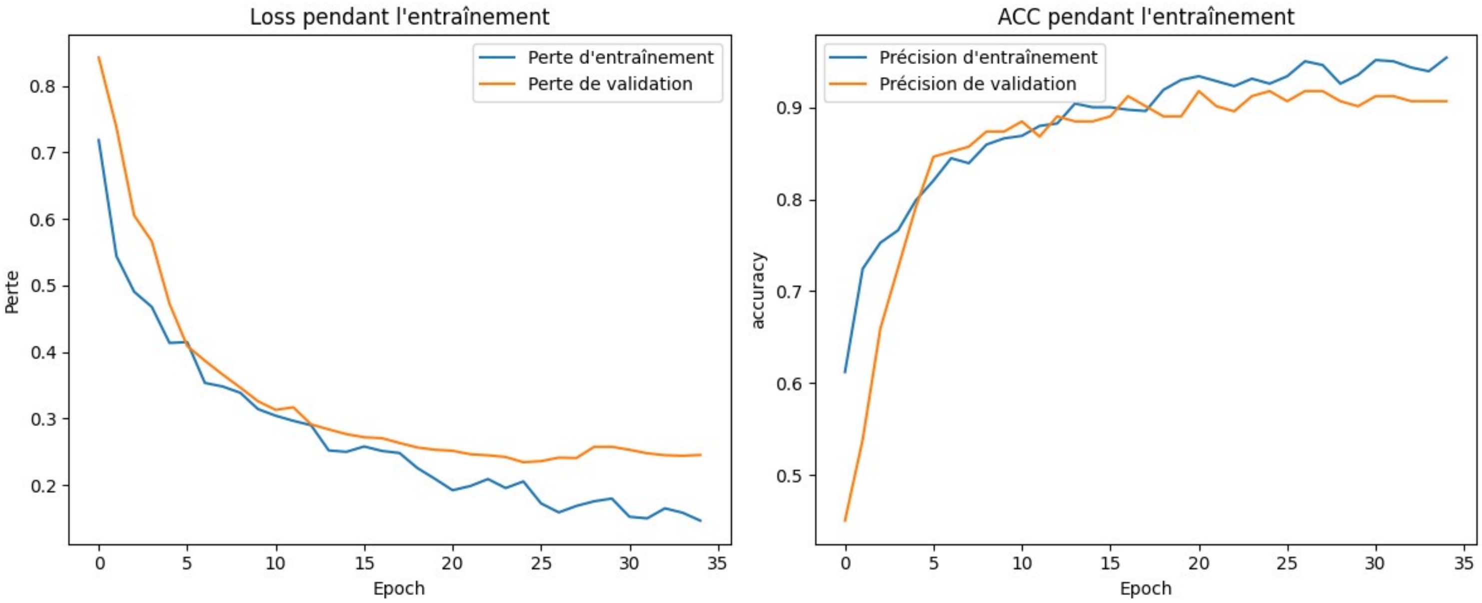
Each phase of this process was vital to ensuring the quality and reliability of our model, enabling accurate classification despite the challenges posed by the diversity and inconsistency of the initial internet-extracted data.

Training

At the heart of this project lies a rigorous training process that involved evaluating a variety of convolutional neural network architectures and harnessing the power of pretrained models. The fine-tuning of the final layers was specifically aligned with the idiosyncrasies of our data. A defined confidence threshold was implemented to filter the dataset, which allowed us to discard dubious images and increase the reliability of our training. Our experiments were supported by frameworks such as TensorFlow and PyTorch, incorporating renowned models like ImageNet and YOLO to test their effectiveness.

The learning curves show a stable and promising convergence, suggesting that the model consistently and reliably improves over time. The consistency between training loss and validation accuracy indicates that the model is neither underfitting nor overfitting.

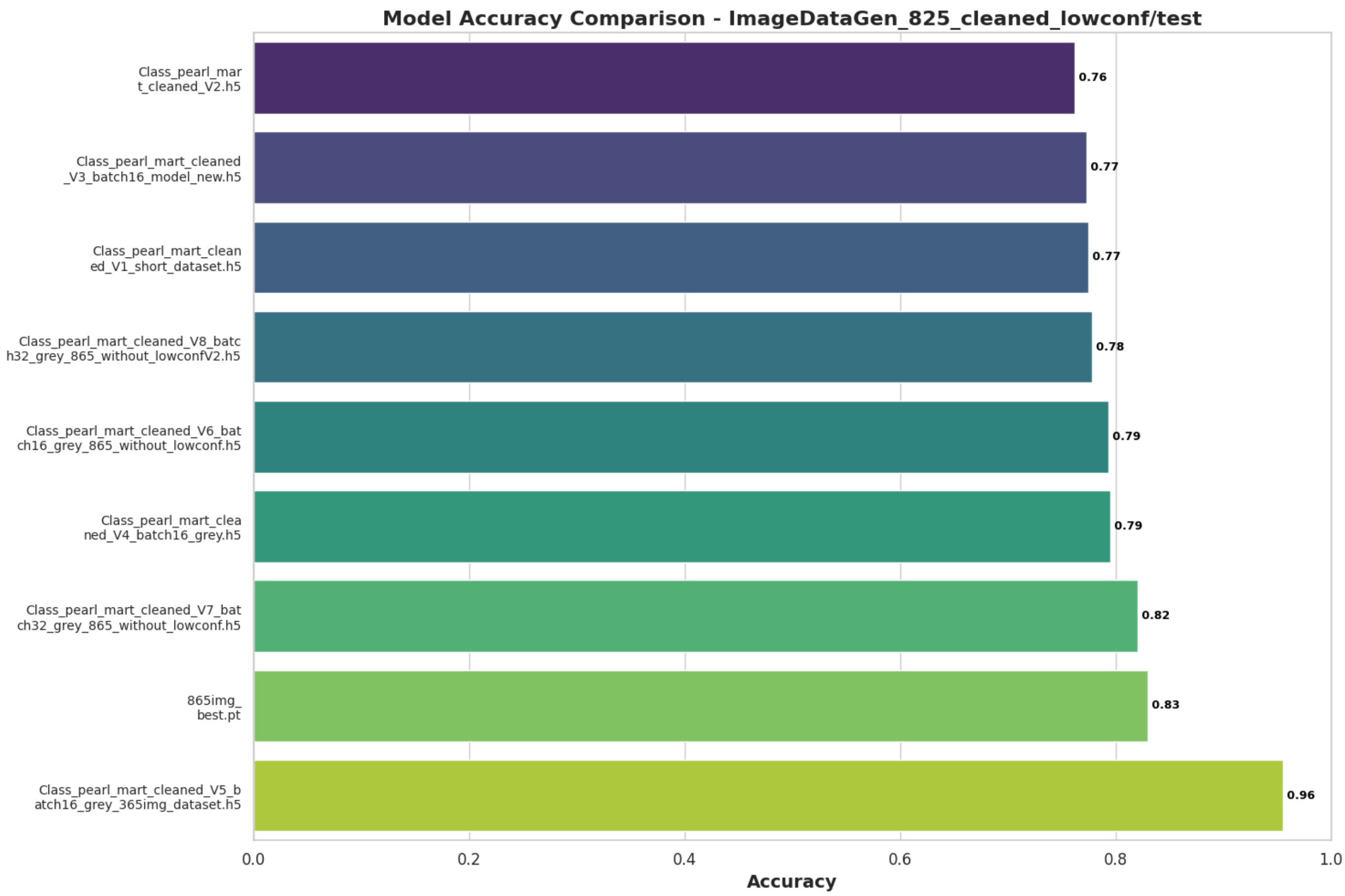




Results

The initial results reveal a significant increase in accuracy with each iteration, validating the efficacy of our methodical approach. Comparative graphs provide a tangible visualization of the evolution and adaptability of our models across different datasets. In particular, comparative images highlight the superiority of the most recent versions of our models.

These advances testify to the remarkable ability of deep learning to accurately and effectively interpret data, which, despite being heterogeneous and from varied sources, can be transformed into precise and reliable insights. This demonstrates the potential of deep learning to adapt and excel even when the initial data presents challenges in terms of quality and consistency.



Summary of the Martensitic and Pearlite Microstructures Classification Project

This project aims to accurately classify martensitic and pearlite microstructures by leveraging data accessible on the Internet. Navigating the inherent challenges posed by the variability of online data, this work utilizes convolutional neural networks and finely tuned pretrained models to recognize and classify the two structures. The rigorous methodology includes image scraping, upscaling, automatic cropping, and meticulous data selection for training. The approach, tested on robust frameworks such as TensorFlow and PyTorch, has yielded encouraging results, progressively improving accuracy and demonstrating the capability of deep learning to provide meaningful insights from imperfect data. This work showcases the evolution and flexibility of deep learning models in the face of data diversity, thus offering new perspectives for computer vision applications in metallurgy, even without the necessity of having vast amounts of data.