

Machine Learning Approaches in Agile Manufacturing with Recycled Materials for Sustainability

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Abstract

It is important to develop sustainable processes in materials science and manufacturing that are environmentally friendly. AI can play a significant role in decision support here as evident from our earlier research leading to tools developed using our proposed machine learning based approaches. Such tools served the purpose of computational estimation and expert systems. This research addresses environmental sustainability in materials science via decision support in agile manufacturing using recycled and reclaimed materials. It is a safe and responsible way to turn a specific waste stream to value-added products. We propose to use data-driven methods in AI by applying machine learning models for predictive analysis to guide decision support in manufacturing. This includes harnessing artificial neural networks to study parameters affecting heat treatment of materials and impacts on their properties; deep learning via advances such as convolutional neural networks to explore grain size detection; and other classifiers such as Random Forests to analyze phase fraction detection. Results with all these methods seem promising to embark on further work, e.g. ANN yields accuracy around 90% for predicting micro-structure development as per quench tempering, a heat treatment process. Future work entails several challenges: investigating various computer vision models (VGG, ResNet etc.) to find optimal accuracy, efficiency and robustness adequate for sustainable processes; creating domain-specific tools using machine learning for decision support in agile manufacturing; and assessing impacts on sustainability with metrics incorporating the appropriate use of recycled materials as well as the effectiveness of developed products. Our work makes impacts on green technology for smart manufacturing, and is motivated by related work in the highly interesting realm of AI for materials science.

Introduction

The role of AI in the overall realm of sustainability is critical in recent times. This is because we truly need to live in a green, clean and sustainable manner in order to save the planet, wherein machine learning techniques can help to make adequate predictions for decision support in scientific processes. This is pertinent to various scientific domains as evident from a plethora of studies in the litera-

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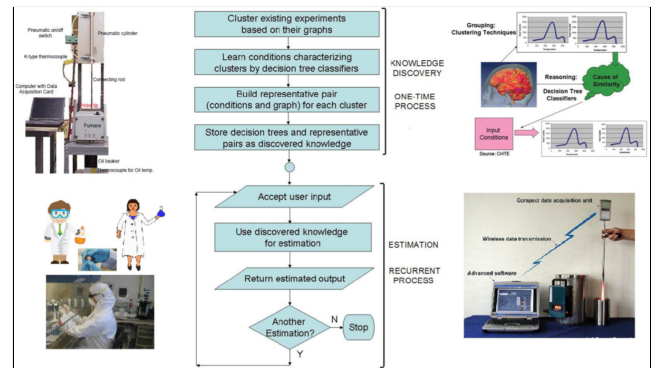


Figure 1: AutoDomainMine for computational estimation

ture (Butler et al. 2018), (Kotthoff et al. 2022), (Nishant, Kennedy, and Corbett 2020), (Ai et al. 2011), (Hutter, Kotthoff, and Vanschoren 2019), (Rajasekar and Weng 2009), (Liu et al. 2022), (Tsolakis et al. 2021), (Weikum et al. 2021), (Zaki, Ramakrishnan, and Zhao 2010), (Zadeh, Abbasov, and Shahbazova 2015). In this paper, we address the domain of Materials Science & Manufacturing, claiming that sustainable processes are imperative.

More specifically, our problem is defined as follows. There is a necessity to develop agile manufacturing techniques using recycled & reclaimed metals. It is a safe & responsible method of turning a specific waste stream to value-added products, in line with environmental sustainability. Note that agile manufacturing is “a manufacturing methodology that places an extremely strong focus on rapid response to the customer - turning speed and agility into a key competitive advantage” (Lean-Production 2011). Therefore, agile manufacturing is a recommended approach for acquiring a “competitive advantage in the fast-moving marketplace” of the modern day. We investigate the contributions of AI here, for developing tools based on machine learning to advance sustainable agile manufacturing.

Earlier Research: AutoDomainMine

In our earlier research overlapping AI and Materials Science, we addressed the problem of developing a computa-

tional estimation approach such that: (1) given some or all of the input conditions of an experiment, it should display the most likely resulting graph; (2) given desired graph in an experiment or ranges describing its features, it should determine the most appropriate input conditions to achieve it. Our proposed solution entailed an approach called AutoDomain-Mine to automate a typical learning strategy of scientists via an integrated framework of data mining techniques (see Figure 1) (Varde et al. 2006). This approach obtained desired levels of accuracy acceptable for targeted applications. The estimation needed far less time than lab experiments saving significant time & resources. Domain knowledge was incorporated within AutoDomainMine & its sub-processes to make them more meaningful for computational estimation. The resulting tool “AutoDomainMine” was found extremely useful (Varde, Rundensteiner, and Sisson 2007). A journal article was recently authored based on its test-of-the-time success story due to numerous citations in CS & Materials Science, as well as practical usefulness (Varde 2022).

Motivated by AutoDomainMine and other such success stories harnessing AI techniques in various scientific domains & applications (Varde et al. 2007), (Pawlish and Varde 2010), (Varde 2009), (Puri et al. 2018), (Basavaraju and Varde 2017), (Du et al. 2020), (Pathak et al. 2019) we propose AI-related approaches for sustainable manufacturing in our current research as described next.

Proposed Approaches

Our work spans developing data-driven methods and tools to enable rationally designed production. In this respect, we have recently developed machine learning based tools to predict the mechanical properties of steel alloys based on compositions, heat treatments and microstructures (Wang et al. 2021). We have also contributed to adapting machine learning related models for predicting the influence of heat treatments on the tensile properties of Ti6Al4V parts prepared by selective laser melting (Wang et al. 2022). Note that Ti6Al4V is an “alpha-beta titanium alloy with a high specific strength and excellent corrosion resistance” (Wikipedia 2022). It among the popular titanium alloys useful in situations where “low density and excellent corrosion resistance” are important, e.g. aerospace applications as well as bio-mechanical devices such as dental implants, hip & knee joints etc. Some of our work in this context entails estimating the tensile properties of annealed Ti6Al4V parts manufactured via selective laser melting (Yang et al. 2022). This research makes impacts on sustainable manufacturing.

In line with such work, we study the recommended breakdown of metal waste recipe at forward operating bases, as depicted in Figure 2. We aim to progress from waste metal to weapons, thus conducting additive manufacturing enabled agile manufacturing (Liang 2022). We propose a data-driven analysis method, an overview of which is illustrated in Figure 3. Modeling to optimize heat treatment parameters occurs as in Figure 4. ANNs (Artificial Neural Networks) are deployed for this purpose. Microstructure prediction using a suitable ANN topology is synopsised in Figure 5.

We conduct further microstructure analysis by adapting deep learning and other classifiers in machine learning.

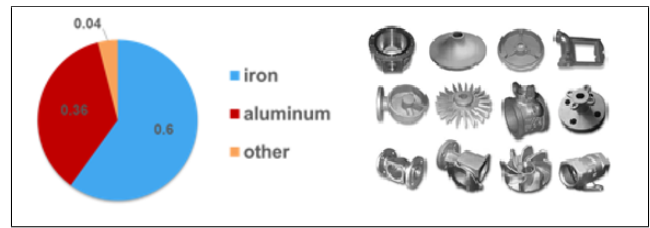


Figure 2: Metal waste and its breakdown

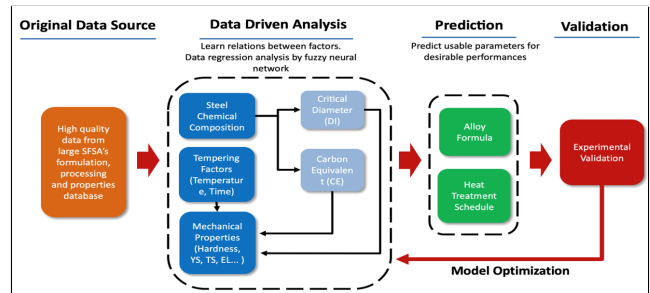


Figure 3: Procedure for analysis

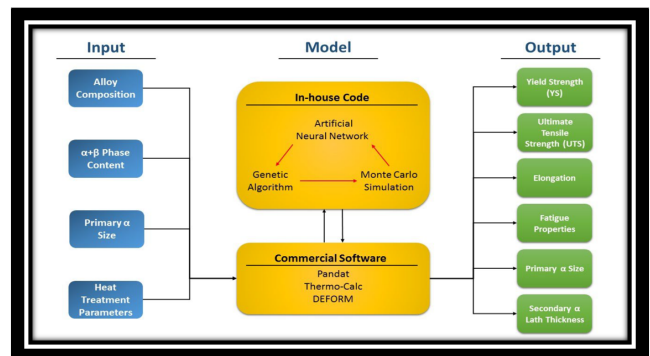


Figure 4: Modeling with machine learning techniques

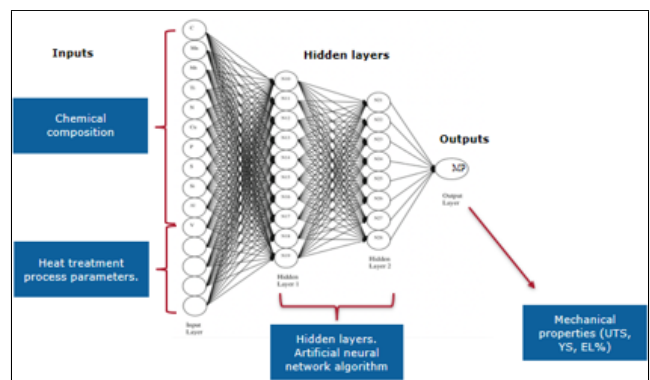


Figure 5: ANN: predict mechanical properties of steel alloy

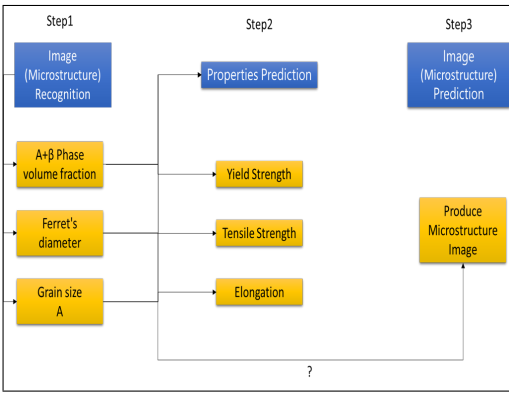


Figure 6: Phase fraction detection by Random Forests

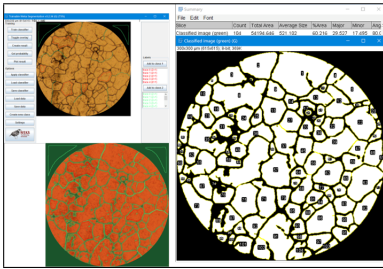


Figure 7: Grain-size detection by CNN

Deep learning occurs with CNNs (Convolutional Neural Networks) to augment the accuracy for learning at a finer level of granularity. Additionally, we deploy RF (Random Forests) as classifiers to enhance interpretability and explainability. Figure 6 portrays an example of phase fraction detection by utilizing the RF classifier. Grain-size detection by harnessing CNN is exemplified in Figure 7.

Likewise, much analysis occurs using various machine learning paradigms in order to guide manufacturing processes for agile as well as sustainable technologies. Machine learning models help to estimate certain tendencies in advance, predict the occurrence of specific phenomena, and thereby assist in decision-making. For instance, if scientists can gauge that a particular combination of input conditions leads to a resulting microstructure in terms of grain-size and other parameters based on discovering knowledge from CNN outputs, they can use that knowledge to make decisions about selecting the corresponding input conditions in real industrial processes and hence advise the concerned working professionals. Thus, in order to conduct manufacturing in an agile sustainable manner, scientists and industrial professionals can plan accordingly by conserving time and resources, using recycled materials, waste products etc. so as to obtain the desired results efficiently. Since the large amounts of data obtained from previously conducted laboratory experiments is used to train the machine learning models rigorously, these models can provide adequate predictive analysis for decision support in real industrial processes. Hence, machine learning can be used to guide agile sustainable manufacturing by acquiring knowledge from existing

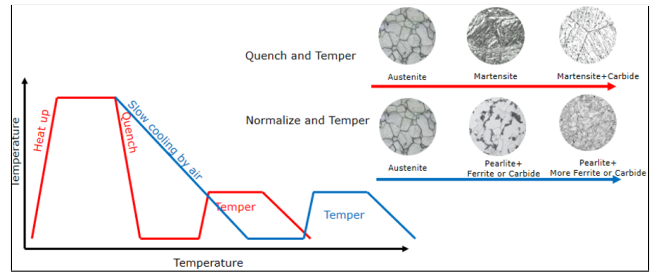


Figure 8: Quench & temper, Normalize & temper

data and using that to support further decision-making, enhancing accuracy, efficiency as well as clean production.

Experimental Results

We present a summary of our exhaustive experimentation in connection with machine learning for agile sustainable manufacturing. Laboratory studies on microstructure development in Quench & Temper (QT) as well as Normalize & Temper (NT) are used as the basis for learning in ANN experiments. Quenching is a process entailing the rapid cooling of a material in a liquid or gas medium to obtain desired mechanical properties. Tempering, on the other hand, heats the material to a high temperature prior to cooling it via different media, thereby contributing towards decreasing its internal stresses and minimizing its brittleness (Eaton-Steel 2016). Normalizing is a related process wherein the steel is heated to a high temperature and thereafter subjected to slow cooling down to room temperature. This heating and slow cooling alters its microstructure, decreases its hardness and raises its ductility (Thermex-Metal 2017). Figure 8 presents examples of our experiments pertaining to these processes.

The ANN prediction results, based on using training data from these processes, are synopsised in Figures 9 and 10. More specifically, Figure 9 plots the true values versus the predicted values, considering chemical composition only, as per the ANN experiments on Ultimate Tensile Strength (UTS) for Quench & Temper (QT). On a related note, Figure 10 presents a chart of the count versus prediction error in the ANN experiments on UTS for QT. It is observed that the standard error of estimate is 9.81 ksi (kilo pounds per square inch) in this example. Likewise, numerous experiments are conducted using machine learning paradigms such as ANN. Domain experts infer that the results obtained from such experiments are accurate and efficient for predictive analysis. Hence, such studies can be useful to guide decision-making in the corresponding real industrial processes to aid agile sustainable manufacturing. For instance, in some earlier work, we developed an expert system called QuenchMiner (Varde et al. 2003) in the context of heat treatment processes, analyzing tendencies such as distortion, part hardness in quenching etc. thereby guiding decision support in heat treatment analogous to a real human expert. Likewise, results from our experiments here can pave the way for building tools to aid agile sustainable manufacturing.

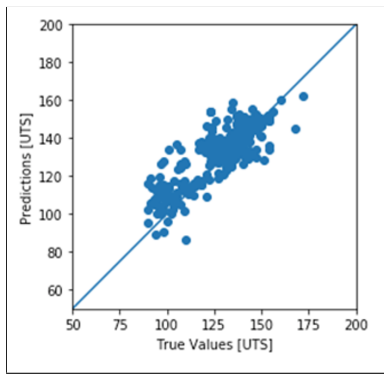


Figure 9: ANN modeling results: True values vs. prediction (by chemical composition only)

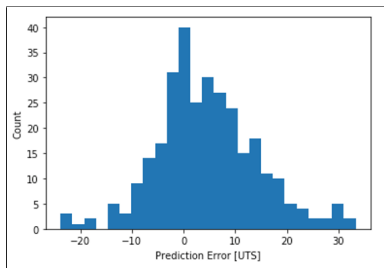


Figure 10: ANN modeling results: Count vs. prediction error - Std. error of estimate is 9.81 ksi (kilo pounds per sq. inch)

Related Work

There is much work overlapping AI and Materials Science as well as AI and environmental sustainability. Optimization of laser-induced graphene production is proposed in a recent study (Kotthoff et al. 2022) by generating a series of unique datasets for machine learning with challenges related to behavioral modeling, knowledge transfer and production parameters. The role of data mining and machine learning methods such as decision tree classifiers and case-based reasoning is explored with respect to the greening of data centers (Pawlish and Varde 2010). ANN based solutions are investigated in a recent PhD dissertation (Yang 2021) within Mechanical Engineering, in the heat treatment of materials.

On a related note, since there are images involved in many scientific experiments, it is important to analyze them vis-a-vis domain expert reasoning. An interesting piece of research proposes a technique called FeaturesRank (Varde et al. 2007) to learn the relative importance of various features in scientific images, including those at nanoscale levels. Considering a more generic perspective, AI researchers propose an approach called YOLO (You Only Look Once) for fast real-time object detection, addressing 9000+ object categories (Redmon and Farhadi 2016). Furthermore, the fusion of vision and language is proposed in the context of object recognition (Shiang et al. 2017), presented at AAIL. These and other studies in object identification and image classification are highly significant in scientific domains because they help in efficient analysis of a large number of im-

ages from lab experiments and industrial processes, thereby aiding scientists in decision-making.

Moving forward, commonsense knowledge can be crucial in various AI-related applications as elaborated in the works of many researchers (Tandon, Varde, and de Melo 2017), (Davis and Marcus 2015), (Ilievski et al. 2021), (Razniewski, Tandon, and Varde 2021), (Kaiser et al. 2014), (Nguyen, Razniewski, and Weikum 2021). Some of these pertain to science and engineering domains. We humans have inherent common sense that helps us distinguish objects within images, and associate everyday facts with scientific concepts, in order to assist our natural decision-making even in situations encountered for the first time. Since huge amounts of prior training data may not always be available, it is advisable to complement the learning of any AI-based systems with knowledge bases incorporating commonsense knowledge. State-of-the-art systems such as TupleKB (Mishra, Tandon, and Clark 2017) and Arc (Clark et al. 2018) provide commonsense knowledge bases, and aid in commonsense reasoning pertinent to scientific facts; hence they can be used in conjunction with various AI systems.

Considering various such related work, our research in this paper makes a contribution towards AI and Materials Science with a view to aiding sustainability and helping in the overall vision of saving the planet. Our approaches that aim to use recycled & waste materials in agile sustainable manufacturing, relying on machine learning techniques for predictive analysis, make impacts on green and clean manufacturing, thus being in line with sustainability.

Conclusions and Open Issues

In conclusion, we re-emphasize that our prior work on AutoDomainMine for computational estimation motivated this research, encouraging us to pursue further studies. Related work by many researchers in AI, Materials Science and sustainability provided further inspiration to conduct studies on agile sustainable manufacturing. In this paper, we aim to reuse recycled and waste materials from forward operating bases, in order to generate valuable products (for use in weaponry to aid defense operations), thereby making positive impacts on environmental sustainability. We explore machine learning techniques such as ANN, RF and CNN using real data from lab experiments in order to conduct predictive analysis to guide decision support in industrial manufacturing processes. Our ANN results incur accuracy around 90%, high efficiency, and low costs (lab experiment costs only). CNN and RF also provide accuracy in a very high range, aiding deeper analysis on a finer-level, and better comprehensibility for explainable AI, respectively.

Future challenges include investigating computer vision models such as VGG, ResNet etc. to potentially enhance accuracy, efficiency and robustness. We aim to build tools using machine learning for decision support in agile manufacturing. We also plan to assess the precise impacts on sustainability by proposing and deploying adequate metrics based on the use of recycled materials, and the effectiveness of developed products. In general, this work treads the bridge connecting AI and Materials Science, while also making positive impacts on environmental sustainability.

Acknowledgments

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