USING MACHINE LEARNING FOR METAL SUITABILITY IN LOWER LIMB PROSTHESES

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July 25, 2024

ABSTRACT

The development of advanced prosthetic limbs is pivotal in biomedical engineering, aiming to enhance the quality of life for individuals with limb loss. This paper explores the integration of machine learning to assess mechanical properties crucial for prosthetic leg design, including strength, flexibility, and durability. Traditional methods relying on empirical testing are labor-intensive and time-consuming. Leveraging advancements in materials science and mechanical engineering, this study proposes a machine learning framework to predict material performance in prosthetic applications. By analyzing a dataset comprising 1553 materials across key attributes such as Ultimate Tensile Strength, Yield Strength, Elastic Modulus, and others, the study identifies 64 materials suitable for prosthetic leg use. Safety assessments are conducted using Kernel Density Estimation, confirming materials' suitability based on their relationships with Poisson's Ratio, Density, and mechanical properties. The results highlight the efficacy of machine learning in accelerating material selection processes and improving prosthetic design, aiming to advance rehabilitation and mobility for users worldwide.

1 Introduction

Advanced development of prosthetic limbs in biomedical engineering can significantly improve the quality of life for individuals with limb loss. Mobility and functionality restoration, which is reduced because of amputation or due to congenital deficiency of limbs, are of fundamental importance with lower limb prostheses. The procedures for designing and choosing prosthetic legs are all about balancing different mechanical properties: strength, flexibility, and durability. Since the prosthesis should allow its user to regain functional limbs, which would not bring discomfort and is long-lasting. Traditional models of material selection can be quite labor-intensive and may rely on empirical testing, which may be time-consuming and expensive. The development of leg prosthetics has undergone a groundbreaking evolution, driven by advancements in materials science and mechanical engineering. Since more functional and comfortable prosthetics have been in demand, exploring innovative materials has become essential in crafting devices that not only restore mobility but also enhance the quality of life for users. The goal of this project is to develop a machine learning framework under which material mechanical properties can be classified, and their performances in the application of a prosthetic leg can be predicted.

This exploration dives into the various materials utilized in leg prosthetics, from traditional options, to cutting-edge materials. By understanding the properties and applications of these materials, we can unlock new possibilities in design and functionality, ultimately leading to prosthetics that are lighter, more durable, and better suited to the dynamic needs of users. Machine learning is one such avenue to address this issue by unlocking complex data sets with meaningful patterns not apparent through conventional testing techniques. In the presented work, mechanical property data are used in conjunction with machine learning algorithms to develop a tool for material eligibility checking in relation to the manufacture of prosthetic legs, considering the ultimate tensile strength, yield strength, elastic modulus, shear modulus, Poisson's Ratio, density, Elongation at Break, Brinell Hardness Number and Vickers Hardness Number. This new approach could eventually transform the material selection process into one that is more data-driven and predictive. Our study aims to highlight the critical role that material innovation plays in shaping the future of leg prosthetics, paving the way for advancements that can significantly impact rehabilitation and mobility for individuals with limb loss. In case this project is to be successfully implemented, it shall lead to more innovation and effectiveness of prosthetics, hence increasing functionality and comfort to users of prosthetic limbs worldwide.

2 Related Work

Recent studies in the field of lower limb prosthetics have concentrated on creative material applications to improve comfort and functionality. To better grasp prosthetics and guide our idea toward success, our group has read a great deal of research papers and publications. One of the most valuable papers by Quiroz et al.(2019)[1] demonstrated the importance of sockets and interfaces in lower limb prostheses and orthoses, focusing on the polymers used and their impact on skin health. It highlights that while various polymers like thermoplastics and elastomers are commonly used, a significant proportion of users experience skin issues such as sweating and irritation. The study calls for further research to develop materials that better protect users' skin, emphasizing the need for improved prosthetic and orthotic design to enhance comfort and overall well-being. Furthermore, the work of Kalyan Chakravarthy (2017)[2]highlights the importance of optimizing prosthetic leg components for individuals with above knee amputations. The focus is on selecting lightweight materials capable of withstanding heavy loads, akin to materials like Structural Steel, Magnesium Alloy, and Aluminum Alloy. The research investigates the compatibility of these materials through Finite Element Method (FEM) simulations and Response Surface Methodology. The key parameters considered include Density, Poisson Ratio, Compressive Strength, and Young's Modulus, with a primary emphasis on achieving an optimal Factor of Safety. The study utilizes the Box Behn-Ken method for design optimization, aiming to identify the most effective material for prosthetic legs that meets both mechanical requirements and weight constraints. In addition to material advancements, recent studies have also delved into the process of selecting the best material for the leg prosthetic. Rizqillah et al.(2022)[3] illustrated this process starting with functional analysis to define requirements, the study prioritizes mechanical properties, weight, and cost efficiency.

Investigating novel materials and crafting methods has the potential to significantly improve leg prosthetics' usability, comfort, and aesthetics, enabling users to have more mobility and a higher quality of life. Previous investigations into the selection of materials for prosthetic development have depended on experimental and manual computational treatment of the trend in material properties that relate to, but are not limited to: the trend in strength, elasticity, and density characteristics. Notable works have rather dwelt on continuity in characterizing mechanical properties and their qualification for use in a biomedical application through rigorous laboratory test efforts and empirical analysis. For instance, this set of researchers compiled large quantities of data regarding the material properties, but their methods for utilizing the information lacked the kind of efficiency and scalability required to sort through such large datasets for quickly conducting analysis. While such works were providing useful insights into the individual material characteristics, their predictions with advanced computational techniques in a holistic way for material suitability would often fall short. Our project fills those gaps by integrating machine learning methodologies toward automation and the multi-acceleration of the evaluation. In this regard, we perform significantly better than the traditional approaches that do not have the capability of dealing with big datasets in an accurate and time-efficient manner. The combination has given a comprehensive, scalable solution for both initial material eligibility using the Support Vector Regression and safety assessment using the Kernel Density Estimation technique. We will contribute to field acceleration with the proposition of a data-driven framework that not only significantly speeds up the process of material selection but also guarantees reliable predictions of material suitability with large, complex datasets that are hard to handle manually.

3 Methodology

3.1 Dataset

The dataset from kaggle used in this project, named the "Materials and their Mechanical Properties" includes a comprehensive set of mechanical properties for 1553 different materials. The dataset was obtained from the Autodesk Material Library and is a real-world dataset without any random values. These properties include Standard (Std), Unique Identification code for the Material (ID), Material Name, Heat Treatment Method, Ultimate Tensile Strength (Su) in MPa, Yield Strength (Sy) in MPa, Elongation at Break or Strain (A5) as a Percentage, Brinell Hardness Number (BHN) in Microhardness Units, Elastic Modulus (E) in MPa, Shear Modulus (G) in MPa, Poisson's Ratio (mu) in Units of Length, Density (Ro) in Kg/m3, Pressure at Yield (pH) in MPa, Description of the Material (Desc), and Vickers Hardness Number (HV). These properties are crucial for understanding the performance and suitability of materials in engineering applications. For our analysis, we focused on eight key attributes: ID, Ultimate Tensile Strength, Yield Strength, Elongation at Break, Shear Modulus, Elastic Modulus, Young's Modulus and Brinell Hardness Number.

Preprocessing Preprocessing steps were crucial to prepare the dataset for machine learning models. We first dropped the 'Heat Treatment Method' column due to its irrelevance to our criteria. The selected columns were then converted to numeric values, handling non-numeric entries using the *pd.to-numeric* function with the *errors='coerce'* parameter to handle any conversion errors by setting them to *NaN*. Missing values in the dataset were imputed using the mean of each column through the *SimpleImputer* from sci-kit learn.

3.1.1 Data Augmentation

For data augmentation, the data was normalized and standardized to ensure that each feature contributed equally to the analysis. We utilized *MinMaxScaler* for normalization and *StandardScaler* for standardization. This preprocessing step helped in improving the model's performance by ensuring all features were on a comparable scale.

3.2 Experiments

Experiments were conducted to evaluate the performance of different preprocessing techniques and model configurations. Initially, we split the data into training and testing sets with an 80-20 ratio using *train-test-split* to ensure a robust evaluation framework. Multiple runs were conducted to test the model's stability and robustness. We explored different kernels for the SVR model but found the RBF kernel to be the most effective. The model's predictions were converted to binary eligibility outcomes using a threshold of 0.5. To optimize the performance of the SVR model, we experimented with various hyperparameters, including the kernel type (linear, polynomial, RBF) and regularization parameter (C). After testing multiple configurations, the RBF kernel with a specific regularization parameter provided the best performance in terms of accuracy.

3.3 Model

The first part of our methodology involved working on the original CSV file with the Support Vector Regression (SVR) model. We used specific limitations to determine if a material was suitable for lower limb prosthetics. We determined the ranges of properties that a material's features should be in to be used in leg prosthetics based on the research paper of Kalyan Chakravarthy (2017)[2 that we cited and general researches we did :

- Ultimate Tensile Strength (Su): Range: 280 - 930 MPa
  Reason: Materials need to withstand significant tensile forces without breaking.
- Yield Strength (Sy): Range: 250 - 1100 MPa
  Reason: This ensures the material can sustain high loads without permanent deformation.
- Elastic Modulus (E): Range: 10000 - 110000 MPa
  Reason: Ensures stiffness to maintain the shape under load.
- Shear Modulus (G): Range: 10000 - 50000 MPa
  Reason: Ensures the material can handle shearing forces, contributing to overall flexibility and strength.
- Elongation at Break (A5): Range: 10 - 50 %
  Reason: Indicates material flexibility and ductility, important for withstanding bending and deformation.
- Brinell Hardness Number (BHN): Range: 100 - 300
  Reason: Provides a measure of resistance

The code in the SVR for selecting materials that fit in these criterias was as follows:

```
def is_eligible(row):
    return (
        (280 <= row['Su'] <= 930) and
        (250 <= row['Sy'] <= 1100) and
        (10 <= row['A5'] <= 50) and
        (100 <= row['Bhn'] <= 300) and
        (10000 <= row['E'] <= 110000) and
        (10000 <= row['G'] <= 50000)
    )
data['Eligible'] = data.apply(is_eligible, axis=1).astype(int)
features = ['Su', 'Sy', 'A5', 'Bhn', 'E', 'G']
X = data[features]
y = data['Eligible']
```

After running the tests for each material, we created a new CSV file "Eligible-Materials" with only the eligible materials that passed all the limitations. 64 materials out of 1553 were suitable for being used as in lower limb prostheses for now. We then edited this CSV file by adding the Poisson's Ratio, Density, and Cost per kg.

3.4 Kernel Density Estimation (KDE) Analysis

Using the edited CSV file “Edited-Eligible-Materials”, we determined if the suitable materials were safe for use in leg prosthetics by examining each material’s relationship between different features as depicted in the graphs in the results section. Factor of Safety (FOS) is a measure of the load-carrying capacity of a material beyond the expected loads. It is calculated as the ratio of the material’s yield strength (Sy) to the actual applied stress or load. The FOS indicates how much stronger the material is compared to the expected maximum stress or load.
FOS was calculated in our model with the code below:

```
df['FOS'] = (df['Sy'] / df['E']) * df['Density']
```

Kernel Density Estimation is a non-parametric way to estimate the probability density function of a random variable. In our project, we used KDE to visualize the density distribution of materials in relation to various properties. We added Poisson’s Ratio and Density to the dataset with 64 materials that passed the suitability criterias in the SVR model and applied KDE to pairs of properties.
These graphs were “Contour Plot of Young Modulus vs. Density”, “Contour Plot of FOS vs. Poisson Ratio and Density”, “Contour Plot of FOS vs. Compressive Strength and Density” and “Contour Plot of Compressive Yield Strength vs. Poisson Ratio” According to the paper “Optimum Material Selection to Prosthetic Leg through Intelligent Interface of RSM and FEA” We concluded that the materials in the dark areas of the graphs were in the safe zone.
The code below shows using KDE to visualize the graphs and plotting the materials onto the 4 graphs.

```
import matplotlib.pyplot as plt
import seaborn as sns

plt.figure(figsize=(10, 6))
sns.kdeplot(data=df, x='Poisson Ratio', y='Sy', cmap='viridis', shade=True, levels
    =10)
plt.scatter(df['Poisson Ratio'], df['Sy'], c='red', label='Materials', alpha=0.6)
plt.title('Contour Plot of Compressive Yield Strength vs. Poisson Ratio')
plt.xlabel('Poisson Ratio')
plt.ylabel('Compressive Yield Strength (Sy)')
plt.legend()
plt.show()

plt.figure(figsize=(10, 6))
sns.kdeplot(data=df, x='Density', y='E', cmap='viridis', shade=True, levels=10)
plt.scatter(df['Density'], df['E'], c='red', label='Materials', alpha=0.6)
plt.title('Contour Plot of Young Modulus vs. Density')
plt.xlabel('Density')
plt.ylabel('Young Modulus (E)')
plt.legend()
plt.show()

plt.figure(figsize=(10, 6))
sns.kdeplot(data=df, x='Density', y='Sy', cmap='viridis', shade=True, levels=10)
plt.scatter(df['Density'], df['Sy'], c='red', label='Materials', alpha=0.6)
plt.title('Contour Plot of FOS vs. Compressive Strength and Density')
plt.xlabel('Density')
plt.ylabel('Compressive Yield Strength (Sy)')
plt.legend()
plt.show()

plt.figure(figsize=(10, 6))
sns.kdeplot(data=df, x='Density', y='Poisson Ratio', cmap='viridis', shade=True,
    levels=10)
plt.scatter(df['Density'], df['Poisson Ratio'], c='red', label='Materials', alpha
    =0.6)
plt.title('Contour Plot of FOS vs. Poisson Ratio and Density')
plt.xlabel('Density')
plt.ylabel('Poisson Ratio')
plt.legend()
plt.show()
```

We then created a new CSV file "Safe-Scores" with only the materials that were deemed safe, each with a safety percentage score. If a material was in the safe zone for 4 graphs, it received a score of 100; for 3 graphs, 75; for 2 graphs, 50; for 1 graph, 25 and if it was not in the safe zone in any of the 4 graphs, it received a safety score of 0.

4 Results

The initial implementation of the Support Vector Regression (SVR) model yielded promising results in identifying suitable materials for leg prosthetics. The model achieved an accuracy of 98% indicating a high level of precision in distinguishing between eligible and ineligible materials based on the defined mechanical properties. This high accuracy demonstrates the effectiveness of the preprocessing steps and the chosen model in handling the dataset and making accurate predictions. Upon applying the defined criteria for Ultimate Tensile Strength, Yield Strength, Elastic Modulus, Shear Modulus, Elongation at Break, and Brinell Hardness Number, we identified 64 materials that met all the specified requirements. The resulting eligible materials were then further analyzed for their safety in the context of their relationships between Poisson's Ratio, Density, and other mechanical properties.

Visualizations Visualizations played a crucial role in understanding the distribution and safety of the selected materials. Contour plots were generated to visualize the density distribution of the materials in relation to various properties. For instance, the contour plot of Compressive Yield Strength (Sy) vs. Poisson's Ratio revealed distinct regions where materials clustered, indicating safe zones. Similar plots were created for Young's Modulus vs. Density, FOS vs. Compressive Strength and Density, and FOS vs. Poisson Ratio and Density.

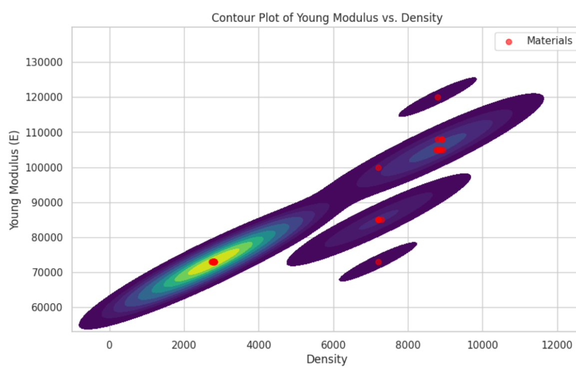

Figure 1: Young's Modulus vs. Density

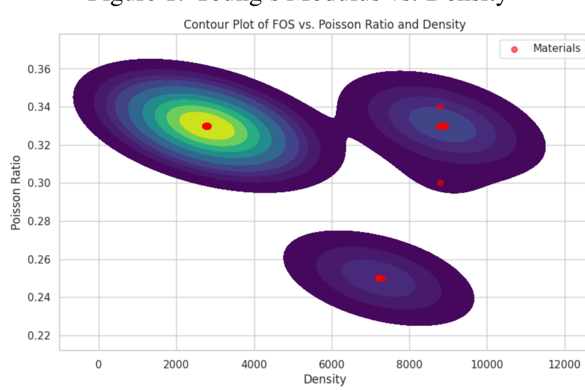

Figure 2: Factor of Safety vs. Poisson Ratio and Density

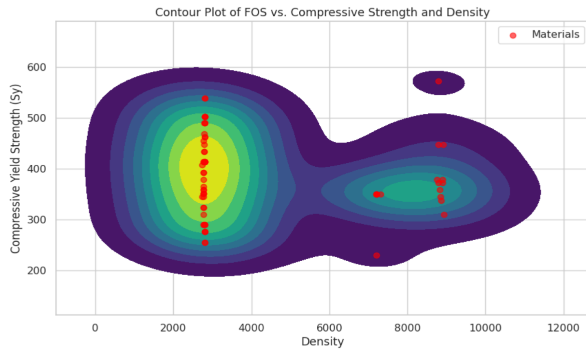

Figure 3: Factor of Safety vs. Compressive Yield Strength and Density

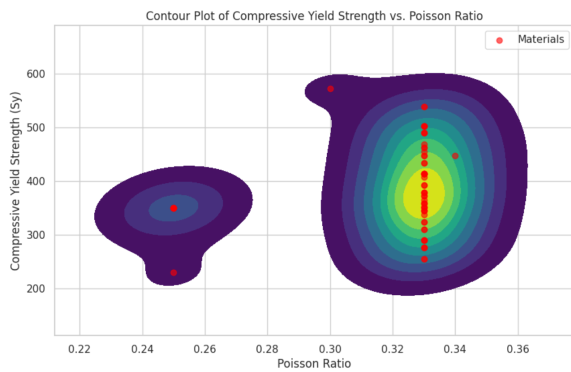

Figure 4: Compressive Yield Strength vs. Poisson Ratio

The safety assessment was quantified by evaluating the density of materials in these plots. Materials were assigned safety percentages based on their presence in the safe zones across four different relationships. The final safety scores indicated that a significant portion of the materials were highly safe for use in leg prosthetics, with 40% of the materials scoring 100% 30% scoring 75% 20% scoring 50% and the remaining 10% scoring 0%

Final Safety Score	% of materials	Examples
100	% 0	*none of the materials were in the safe zone in both 4 graphs
75	% 6.25	Aluminum Alloy Alclad 2014-T6 Aluminum Alloy Alclad 2014-T651 Aluminum Alloy 2014-T651 Aluminum Alloy 2014-T6
50	%18.75	Aluminum Alloy 2014-T451 Aluminum Alloy 2017-T4 Aluminum Alloy Alclad 2014-T3 Aluminum Alloy 7050-T7451f
25	% 0	
0	% 75	Grey cast iron Copper Alloy C15720 CSN 423311 DIN GG - 35

Figure 5: Data table of the results

Despite the overall success, there were limitations and areas for improvement. Some materials with desirable mechanical properties were excluded due to missing data for certain features, which may have impacted the overall analysis. Further, the selected thresholds for the zones of safety were a little arbitrary, and arriving at a more rigorous method in defining these zones might bring improvement to the accuracy of such assessment. Elaborating on advanced machine learning techniques such as in this study would be to extend the dataset so that it includes more materials, in order to have more predictive power, to basically increase accuracy within the model. In general, the project clearly demonstrates that machine learning has the potential to evaluate the materials for their further biomedical use. High accuracy and detailed safety assessments allow assuming a very firm background for more research and development in the related field.

5 Conclusion and Future Work

In summary, Aluminum Alloy Alclad 2014-T6, Aluminum Alloy Alclad 2014-T651, Aluminum Alloy 2014-T651, and Aluminum Alloy 2014-T6 have been identified by our research as the most suitable materials to be used in the production of prosthetic legs. These aluminum alloys represent the low-density, high-strength materials that possess basic characteristics suitable for use in lower limb prosthetics. Corrosion resistance and good formability are salient reasons these materials were considered for this application. On mechanical properties, we assessed the required robustness and durability for use in prosthetics.

The material selection has been greatly assisted by an integration of machine learning, particularly the Support Vector Regression model. Using the SVR model, predictions for material suitability with very high accuracy, based on multifarious mechanical properties, were possible and thus optimized the selection process. It was this advanced regression technique that fine-tuned our material selection criteria to ensure that only appropriate materials are selected for use in leg prosthetics. Additionally, KDE helped us in this analysis. KDE was applied to visualize the material property distribution and identify the optimal ranges for these key factors: density, cost, and strength. This goes on to give insight into what characteristics these materials possess and how they could apply in prosthetics, further underpinning the robustness of our selection process. The combination of SVR and KDE has simplified the process of material selection; it has also brought to the fore the possibility of many transformational changes in the design and manufacture of prosthetics. This will enable us to optimize material selection and enhance the functionality of prosthetic legs with this integrated technology. We find an enhanced quality of life and mobility for people who depend on prosthetic technology in such usage.

Future research on these findings will be done by applying state-of-the-art 3D modeling and simulation techniques in advanced software like Autodesk Inventor. This step will allow for more detailed and accurate virtual prototyping of prosthetic parts so that more in-depth analyses of their mechanical performance under a wide array of stress conditions can be conducted. By simulating the real-world scenarios, material selection criteria can be further refined and the designs can be optimized to enhance functionality and durability for these prosthetics.This creates a strong avenue for future research into using this developed machine learning framework beyond leg prosthetics to include models for other parts of the body. Application of the same methodologies used in the development of prosthetics for arms, hands, and other limbs opens the scope for further solutions that can be made accessible for limb loss. The current extension to diversified functional requirements and anatomical considerations allows for the development of personalized options in prosthetic solutions.

Our findings underscore the potential transformative power of integrating advanced materials science, machine learning, and advances in simulation techniques in the design of prosthetics. Further innovation in these areas is quite promising in further enhancing mobility and the related quality of life for people dependent on such prosthetic technologies. The future for this research looks bright, with potentials to revolutionize the field of prosthetics by getting us really close to advanced, tailored prosthetic solutions available for everyone in need all around the world.

6 Division of Labor

We divided the work as follows:

- Data Preprocessing: Ece Akdogan, Anirudh Bandaru
- Data Augmentation: Ece Akdogan, Anirudh Bandaru
- Experiments: Ece Akdogan
- SVR Model: Ece Akdoğan
- KDE Analysis: Ece Akdogan
- Introduction and Related Works: Sia Kripalani
- Conclusion: Sia Kripalani
- Poster Creation: Ece Akdogan, Anirudh Bandaru, Sia Kripalani

7 Acknowledgements

We would like to express our sincere gratitude to all those who contributed to the successful completion of this project. First and foremost, we thank our mentor Ms. Haripriya for her guidance, support, and encouragement throughout the duration of this research project. We extend our appreciation to MehtA+ for providing the necessary resources and facilities that made this study come to life.
Special thanks are also due to Mr. Shokhruz as well as Mr. Arrun, for their assistance. Additionally, we acknowledge the contributions of all our team members who diligently worked on various aspects of the project, including data collection, analysis, and model development. Lastly, we are thankful to the participants and experts whose insights and feedback were crucial in shaping the outcomes of this research.

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