Optimizing Students' Understanding of the Mechanical Properties of Stainless Steel through Interactive Learning Media based on Machine Learning

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Abstrak

Traditional learning media tends to have limitations in providing interactive experiences that can stimulate better understanding. This is supported by changes in learning styles among students, influenced by extensive exposure to computers and the internet, leading students to prefer learning with the aid of visualizations. This research designs, develops, and tests a machine learning-based visualization tool integrated with the Streamlit framework to enhance students' understanding of the mechanical properties of materials. This visualization tool consists of four main features: data analysis, correlation analysis, 3D visualization, and prediction models using machine learning. The data used for training the machine learning model includes tensile test data of low-alloy steel, comprising mechanical properties, chemical elements, and heat treatment temperatures. The research results indicate that the visualization tool can illustrate the cause-and-effect relationships of parameters influencing the changes in the mechanical properties of low-alloy steel. Each feature in this visualization tool can be utilized to support the analysis of mechanical properties and improve students' understanding of material mechanical properties. Additionally, the visualization tool is evaluated by experts, with information accuracy scoring 4 in the good category, visualization quality at 4.25 in the good category, suitability for learning at 4 in the good category, and ease of use at 4.5 in the good category. Nevertheless, further research and development are needed to test and expand the use of this visualization tool in various learning contexts and other material fields.

Keywords: Optimization, learning media, mechanical properties, stainless steel, machine learning.

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INTRODUCTION

Material science is an interdisciplinary field involving concepts from various branches of science, including physics and chemistry (Coccia, 2020). In mechanical engineering departments, this knowledge is typically acquired through courses in material science and mechanical engineering. This is crucial because mechanical engineering students are expected to have a profound understanding of the mechanical properties of materials. A good understanding of the mechanical properties of materials, especially alloy steel, can reduce the risk of failure in projects such as construction and machine components (Morini et al., 2019), (Leni et al., 2023). Alloy steel is a type of steel obtained by adding specific alloying elements to carbon steel. The added alloying elements, such as chromium, nickel, manganese, vanadium, and others, impart additional properties to the steel, such as strength, corrosion resistance, and high-temperature resistance. Alloy steel is commonly used in situations where strength and resistance to extreme environmental factors are required, such as in the automotive industry, aircraft, construction, and the manufacturing of heavy equipment (Leni, 2023). The choice of alloying elements added depends on specific applications and the desired properties of the steel. However, based on field observations and previous research, it has been found that understanding the mechanical properties of alloy steel is often considered one of the complex and challenging subjects by many students (Mitropoulos et al., 2024), (Vadiraja & Cervantes, 2004). This is attributed to the comprehension of abstract concepts such as heat treatment, chemical composition, plastic deformation, and the use of complex mathematical equations, often lacking tangible visualizations. As a result, students must rely on mathematical representations that can be difficult to grasp. Therefore, there is a need for more interactive learning methods and effective learning media to visualize the factors influencing the mechanical properties of alloy steel.

Traditional learning media tends to have limitations in providing interactive experiences that can stimulate better understanding. In an effort to overcome these limitations, the use of machine learning technology as interactive learning media can be employed as an effective solution. This is supported by changes in learning styles among students, driven by extensive exposure to computers and the internet, leading students to prefer learning with the aid of visualizations. This has prompted educators to adapt teaching methods to align with visual learning that is familiar with technology (Qin et al., 2023). Machine learning is a branch of artificial intelligence that focuses on the development of algorithms and computer models capable of learning from data and making predictions or decisions without explicit programming. In machine learning, computers are taught to recognize patterns, discover relationships, and make decisions based on the experience gained from the provided data (Raschka et al., 2020). Machine learning can be utilized to create an interactive simulation that allows students to directly interact with various factors influencing mechanical properties. Through machine learning, students can observe how changes in the percentage of chemical composition and heat treatment temperature can affect the mechanical properties of alloy steel. This phenomenon, supported by advancements in material science and engineering, has gone through three developmental stages over the years, starting from the experimental stage, theoretical stage, to the simulation-based computational stage(Agrawal & Choudhary, 2016), (Rajan, 2005).

In recent years, the data generated from experiments and simulations has experienced rapid growth, evident in the proliferation of material databases such as Material Project, Computational Materials Repository, Harvard Clean Energy Project, Inorganic Crystal Structure Database, MatMach, and MatWeb (Leni et al., 2023),(Wang et al., 2020). This phenomenon has given rise to the fourth paradigm in material science and engineering, amalgamating the first three paradigms—experimentation, theory, and simulation—into a data-driven scientific discipline (Kalidindi & De Graef, 2015). The application of this paradigm in material science has led to the emergence of a new field known as Materials Informatics.

Materials Informatics is a novel approach in material science that integrates information technology and material science to optimize the process of discovering new materials more efficiently and innovatively (Rajan, 2015), (Frydrych et al., 2021). In Materials Informatics, experimental and simulation data are integrated with data-driven methods such as big data and machine learning to generate deeper insights into material properties (Wei et al., 2019), (Morgan & Jacobs, 2020), (Blaiszik et al., 2019).

The current development of computer technology and data-driven science is progressing rapidly and dynamically. This is propelled by the widespread use of the internet and web technology within academia. This phenomenon enables the integration of learning concepts of material mechanical properties with data, accessible anytime through web-based platforms. Consequently, students can gain direct experience of how changes in one parameter can impact other parameters. Therefore, this research focuses on integrating the latest technology to achieve better learning outcomes, opening new opportunities in curriculum development and learning methods relevant to industry needs.

This research aims to optimize students' understanding of the mechanical properties of stainless steel through the development of interactive learning media based on machine learning. With this approach, it is expected that students can access materials in a more engaging manner, actively participate, and gain a better understanding of the mechanical properties of materials.

METHODS

This study is classified as research and development, aiming to design, develop, and test a visualization tool for the concepts of material mechanical properties based on data. The focus is on creating and evaluating a web-based Exploratory Data Analysis (EDA) tool to visualize the effects of changes in the percentage of chemical elements and heat treatment temperature on the mechanical properties of alloy steel(Liu et al., 2023). In this research, the data used for machine learning modeling consists of tensile test data of low-alloy steel, including chemical elements, heat treatment temperature, and mechanical properties such as Yield Strength, Tensile Strength, and Elongation. The visualization tool is built using the Python programming language, while the web interface is designed using the Streamlit framework (Khorasani et al., 2022), (Nápoles-Duarte et al., 2022)

1. Designing A Machine Learning-Based Visualization Tool.

This visualization tool is designed with four main features: (1) automatic examination of imported data using pandas profiling reports (Wang et al., 2020), allowing users to quickly identify potential errors or anomalies in the dataset; (2) informative visualizations, such as 3D visualization with surface area and contour plots using the matplotlib library; (3) correlation analysis using a correlation heatmap; and (4) predicting mechanical properties using machine learning methods. This enables users to test various scenarios and see how changes in the percentage of chemical elements and heat treatment temperature can affect the mechanical properties of low-alloy steel. The design of this visualization tool consists of two parts: designing and integrating visualization features into the Streamlit-based web framework, as depicted in Figure 1.

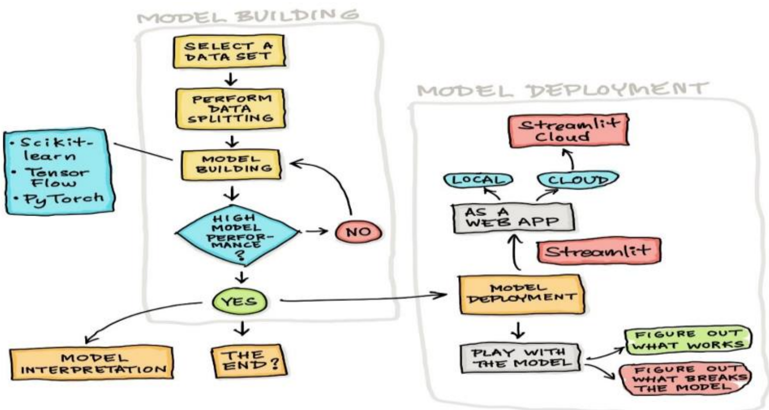

Figure 1. Streamlit-Based Web Framework

In the first stage, the machine learning model was designed using three commonly used algorithms for prediction: Decision Tree (DT), Random Forest (RF), and Artificial Neural Network (ANN). These algorithms were implemented using the default parameters provided by the scikit-learn library version 1.2.2 and Keras version 2.12.0 for ANN. The data used for training and testing the model was divided into two parts: 80% for training data and 20% for testing data (Leni et al., 2024). Each machine learning model was validated using cross-validation, a technique that involves dividing the training data into several different subsets or folds. Iterations were performed on each subset, using it as the test data, while the remaining subsets were used as the training data.

The machine learning models were evaluated using metrics such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R-squared (R2). Model evaluation metrics can be calculated using the following equations (Leni et al., 2023):

a. $$MAE = \frac{i}{N}\sum|y_i - z_i| \quad (1)$$

Where i is the index of the data in the sample, N is the total number of samples, y_i is the actual value of the i-th data, and z_i is the predicted value from the model for the i-th data.

b. $$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(f(X_i) - Y_i)^2} \quad (2)$$

Where n is the number of data points used to test the model, f(X_i) is the value predicted by the model for the i-th data point, and Y_i is the actual value for the i-th data point.

c. $$R = \frac{\sum_{i}^{n}=1(f(X_i)-f(\bar{X}))(Y_i-\bar{Y})}{\sqrt{\sum_{i=1}^{n}(f(X_i)-f(\bar{X}))^2}\sqrt{\sum_{i=1}^{n}Y_i-\bar{Y})^2}} \quad (3)$$

Where f(Xi) is the predicted value of the dependent variable (Y) based on the independent variable (X) for the i-th observation, $f(\bar{X})$ is the average of all predicted values f(Xi) across all observations, Yi is the actual observation value of the dependent variable for the i-th observation, $\bar{Y}$ is the average of all observation values Yi across all observations, and n is the total number of observations.

2. Evaluation

The machine learning-based visualization tool that has been designed will be evaluated through a series of tests involving two main aspects: (1) internal testing to ensure that all functions and components operate as expected, and (2) assessment presented to experts in material science to evaluate the accuracy of information, visualization quality, alignment with educational objectives, and user-friendliness using a Likert scale.

RESULTS AND DISCUSSION

Based on field observations at Muhammadiyah University of West Sumatra in the Mechanical Engineering Department, it was found that the teaching of material science courses mainly focuses on the properties of materials, particularly metal properties. Discussions on the mechanical properties of alloy steel are the most dominant, as a good understanding of the mechanical properties of alloy steel can prevent workplace accidents resulting from material failures. Therefore, in efforts to enhance the quality of interactive digital-based learning media, such as machine learning, planning and methods that align with user needs are required(Kharismatunisa, 2023).

In designing visualization tools for material science learning, especially the mechanical properties of low-alloy steel, the design steps must consider the unique needs in comprehending these complex concepts(Jones & Ashby, 2019). This process involves a deep understanding of the learning material and the best ways to convey information to users in an informative, interactive, and effective manner (Miranda et al., 2021). Before designing visualization tools, a literature review was conducted to gain an in-depth understanding of the mechanical properties of low-alloy steel. This includes analyzing key concepts such as strength, toughness, and elasticity, and considering factors that influence the mechanical properties of stainless steel. According to Castro et al., data can actively play a role as an interactive learning tool. With increasingly sophisticated information technology and visualization tools, students can easily access and visualize tensile test data in the form of graphs, diagrams, and tables. This allows students to observe and understand complex patterns, cause-and-effect relationships, as well as changes in parameters in the mechanical properties of materials. Actively utilizing data in visualization also enables students to explore independently (Stanciulescu et al., 2022), (Cueto & Chinesta, 2023). Moreover, this approach reflects the current trend where data is actively used for decision-making, analysis, and innovation in various industries and disciplines (Aquilani et al., 2020), (Koot et al., 2021).

The dataset used in this research consists of tensile test results on low-alloy steel, including mechanical properties, chemical composition percentages, and heat treatment temperatures. This data was obtained from Kaggle.com, totaling 915 data points with 15 input variables and 3 output variables such as Yield Strength (YS), Tensile Strength (TS), and Elongation (El), as shown in Table 1
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Table 1. Statistics of the Low-Alloy Steel Dataset

Variable	Data Type	Min	Max	Mean
C	Input	0,09	0,34	0,17
Si	Input	0,18	0,52	0,31
Mn	Input	0,42	1,48	0,81
P	Input	0,006	0,03	0,01
S	Input	0,003	0,022	0,01
Ni	Input	0	0,6	0,14
Cr	Input	0	1,31	0,43
Mo	Input	0,005	1,35	0,44
Cu	Input	0	0,25	0,08
V	Input	0	0,3	0,06
Al	Input	0,002	0,05	0,01
Ni	Input	0,0025	0,015	0,01
Ceq	Input	0	0,437	0,09
Nb + Ta	Input	0	0,0017	0,00
Temperature (°C)	Input	27	650	351,60
Tensile Strength (Mpa)	Output	162	6661	496,25

Designing a Machine Learning-Based Visualization Tool

This stage consists of two main phases: the design hase and the integration phase. The design phase includes collecting datasets for machine learning training, data preprocessing, model training, and model evaluation. Figure 2 illustrates the design stage of machine learning.

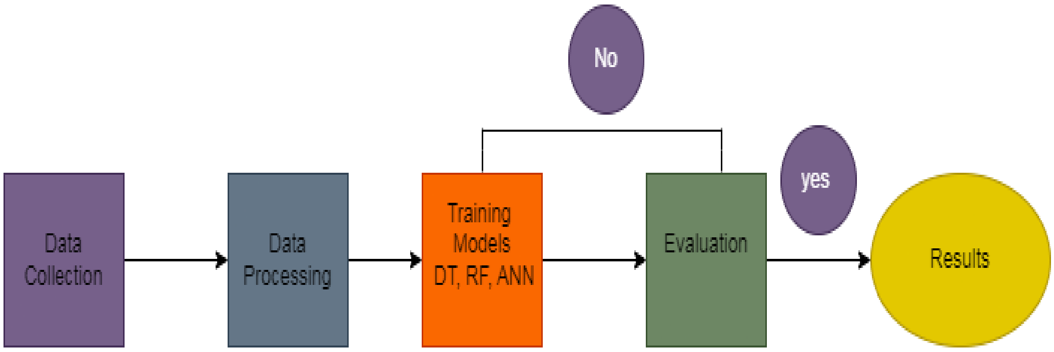

Figure 2. Illustrates the design stage of machine learning.

In this machine learning model, feature selection is performed using Recursive Feature Elimination (RFE) to determine parameters that have the most significant impact on the mechanical properties of low-alloy steel. The results of the feature selection show that there are 7 chemical elements that have a significant influence on the mechanical properties of low-alloy steel, namely Carbon (C), Manganese (Mn), Nickel (Ni), Chromium (Cr), Molybdenum (Mo), Vanadium (V), and Temperature. In addition to improving machine learning performance, feature selection also aims to facilitate students in analyzing parameters that affect the mechanical properties of low-alloy steel. This approach is expected to simplify students' understanding of the most influential factors in altering the mechanical properties of materials. To optimize the model's performance, three different machine learning algorithms are applied to this model: Decision Tree (DT), Random Forest (RF), and Artificial Neural Network (ANN). The implementation of these algorithms is done using the default parameters provided by the scikit-learn library version 1.2.2 and Keras version 2.12.0 for ANN. This approach is designed to provide a consistent and reliable experience in exploring and analyzing data in the context of the mechanical properties of low-alloy steel.

After the design of the machine learning model is completed, the next step is to integrate all visualization tool features into the Streamlit-based web framework. This visualization tool comprises four main features: (1) visualization feature, (2) correlation analysis feature, (3) 3D visualization feature, and (4) machine learning feature. The visualization tool has an interface consisting of a sidebar and a content page, where the sidebar serves as navigation for feature selection. The integration of data visualization features into the Streamlit framework, as depicted in Figure 3, offers a deep and structured understanding of the mechanical properties of low-alloy steel. This visualization feature not only facilitates users in exploring the dataset but also provides a rich and informative visual foundation to support learning concepts of mechanical properties of materials. In order to enhance the utility of this visualization tool as a learning support, an automatic data inspection feature using the pandas profiling module is included. Therefore, users can quickly and efficiently identify potential errors or anomalies in the dataset, opening opportunities for deeper learning and better understanding of the conditions and characteristics of the mechanical properties of low-alloy steel.Furthermore, this visualization tool also presents visual diagrams such as boxplots, scatterplots, and line plots through the matplotlib library. The presence of these diagrams provides an interactive visual dimension, allowing users to clearly see data distribution, relationships between variables, and trends in changes in mechanical properties that can aid their learning process. Thus, this visualization tool is not just a data exploration platform but also an engaging and informative learning tool related to the mechanical properties of low-alloy steel.

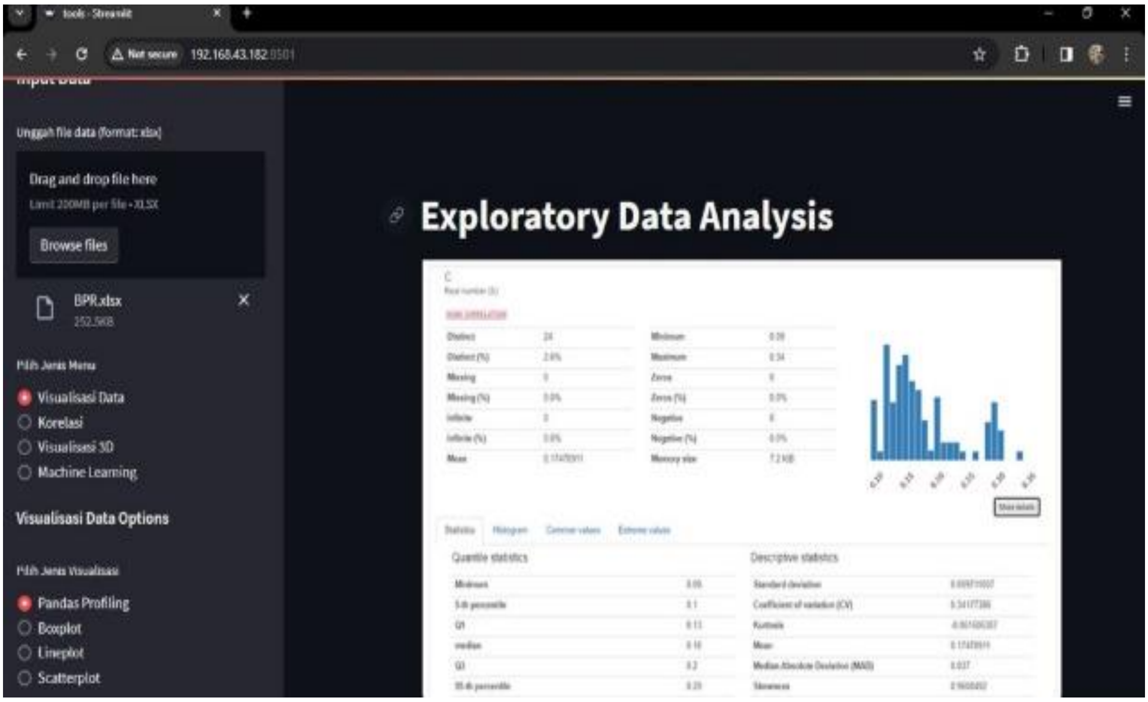

Figure 3. Display of Data Visualization Features

In the second feature, there is a correlation feature, which is designed to observe the relationship between each variable that will be analyzed. In this study, the correlation analysis utilized a correlation heatmap calculated using the Pearson correlation equation. The Pearson correlation equation provides values between -1 and 1, where a value of 1 indicates a perfect positive correlation (when one variable increases, the other also increases linearly). A value of -1 indicates a perfect negative correlation (when one variable increases, the other decreases linearly), and a value of 0 indicates no linear correlation(Abounaima et al., 2020). This technique helps illustrate the relationships between variables in a dataset in a more visual and digestible manner(Gu, 2022). With the presence of this correlation feature, it is expected that users, especially students studying the mechanical properties of low-alloy steel, can more easily identify and understand the extent to which these variables are interconnected (Toumpis, 2015). This provides a solid foundation for conducting further analysis and deepening understanding of the changes in mechanical properties of the material. The display of the correlation feature can be seen in Figure 4.

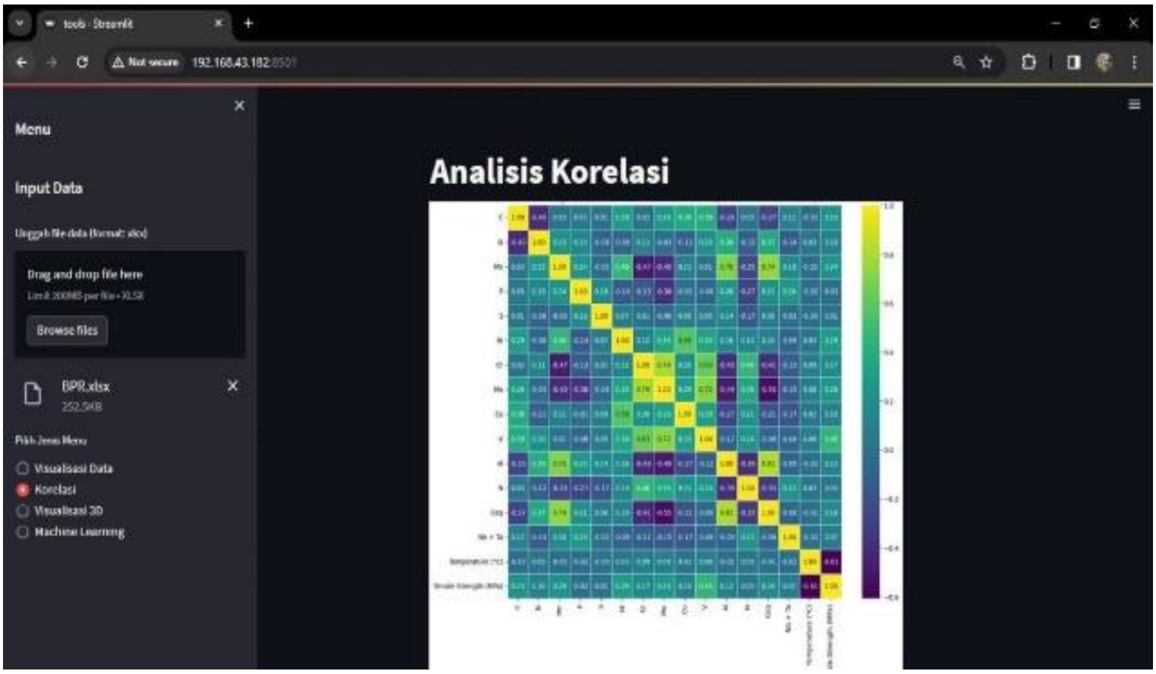

Figure 4. Correlation Analysis Feature

In the next feature, there is a specific aspect that involves visualization using 3D graphics with the matplotlib library. This feature creates two types of 3D graphics that play a significant role in supporting the learning of the mechanical properties of low-alloy steel, namely surface area and contour plot. The presence of 3D graphics in this feature is not merely decorative but serves as a strategic tool to enhance students' analytical abilities in understanding the changes in the percentage of chemical elements accompanied by other variables. 3D graphics play a central role in providing a deeper understanding of the impact of changing parameters on the mechanical properties of low-alloy steel. With the availability of two types of 3D graphics, namely surface area and contour plot, students can more effectively visualize and analyze how combinations of specific parameter values can affect the mechanical properties of the material. Additionally, 3D graphics serve as a valuable learning tool by enabling students to directly examine the effects of variations in chemical elements and heat treatment temperature parameters on the mechanical properties of low-alloy steel. Thus, this visualization feature not only supports informative learning but also facilitates students in conducting analyses of parameter value combinations to achieve the desired optimization of mechanical properties (Kuosa et al., 2016). The display of the 3D visualization feature can be seen in Figure 5.

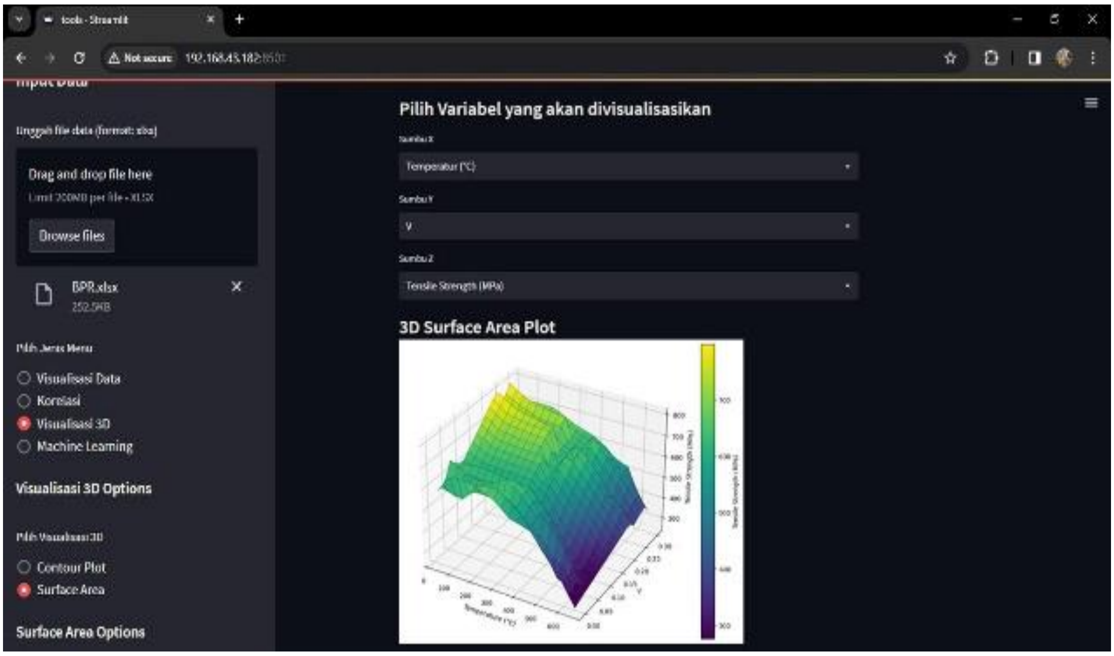

Figure 5. Display of 3D Visualization Feature

The last feature in this visualization tool is the prediction model that leverages machine learning technology. This feature not only provides students with the ability to predict critical mechanical properties of low-alloy steel, such as Yield Strength (YS), Tensile Strength (TS), and Elongation (El), but also opens the door for deeper exploration of how variations in the percentage of chemical elements and heat treatment temperature can impact these three mechanical properties (Horath, 2019). In its use, students can easily input the percentage of chemical elements and heat treatment temperature according to the predefined scale of values. The prediction results are then automatically displayed in the form of a table available on the page, providing a clear visualization of the impact of parameter changes on the mechanical properties of low-alloy steel (Chen et al., 2024). The sidebar section of this tool's interface provides flexibility for students to switch between algorithm types according to user needs and preferences. Thus, the prediction model feature not only serves as a tool for analyzing predictions of mechanical properties but also as a means that provides space for students to explore and understand the influence of machine learning algorithms in the context of learning the mechanical properties of low-alloy steel (K. Guo et al., 2021). With this feature, it is expected that students can sharpen their analytical skills and develop a deeper understanding of the mechanical properties of materials

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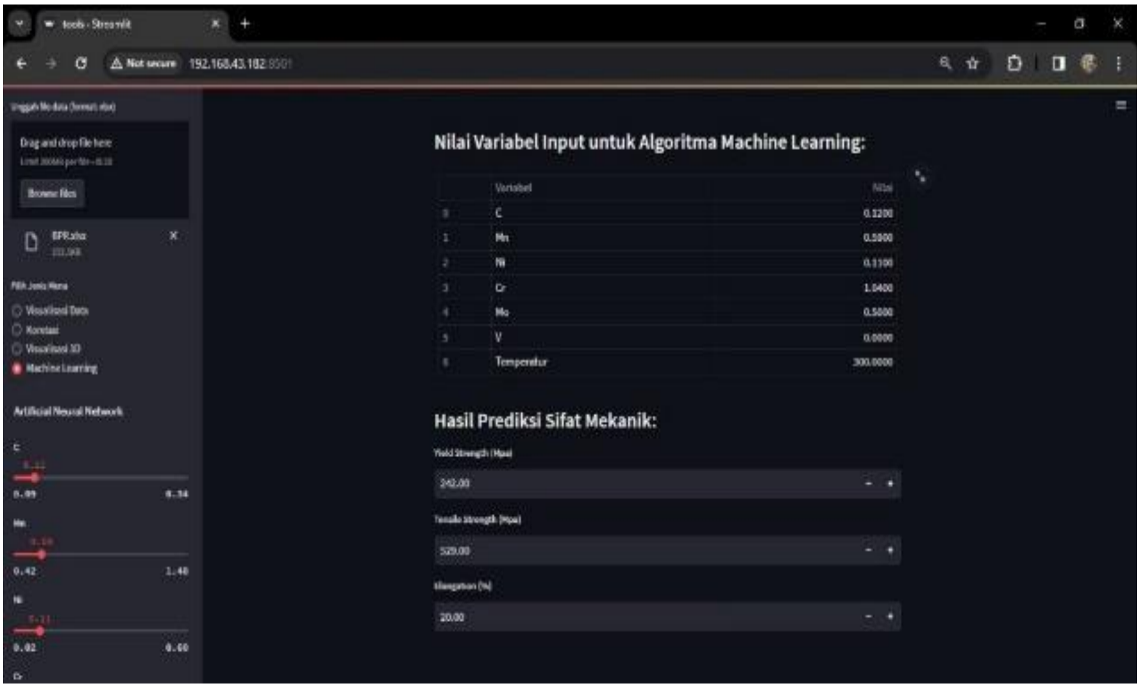

Figure 6. Display of Machine Learning Feature

1. Evaluation of Visualization Tool

Evaluation of the visualization tool for the concept of mechanical properties of materials is conducted through two main aspects: internal testing and assessment by experts. Internal testing is a crucial step to ensure that the visualization tool functions as expected and operates well. This internal testing process involves verifying the functionality of each tool component, ensuring the operability of all features, and checking for quick and responsive responses to user input (Y. Guo et al., 2009). The results of internal testing indicate that the visualization tool operates optimally. Quick responses to user input, visualization loading times, and transitions between features are within an acceptable range. Additionally, the visualization tool demonstrates good stability, experiencing no crashes or repeated errors during the testing process. Its ability to integrate data from various sources, including student simulation and experimental data, is also confirmed accurately.

The next stage involves the assessment of the visualization tool by experts using a Likert scale. Assessment aspects include the accuracy of the presented information, visualization quality, alignment with educational aspects, and ease of use of the visualization tool. The assessment is carried out by four lecturers who have taught related courses at the University of Muhammadiyah West Sumatra. The results of the expert assessment can be seen in Figure 7.

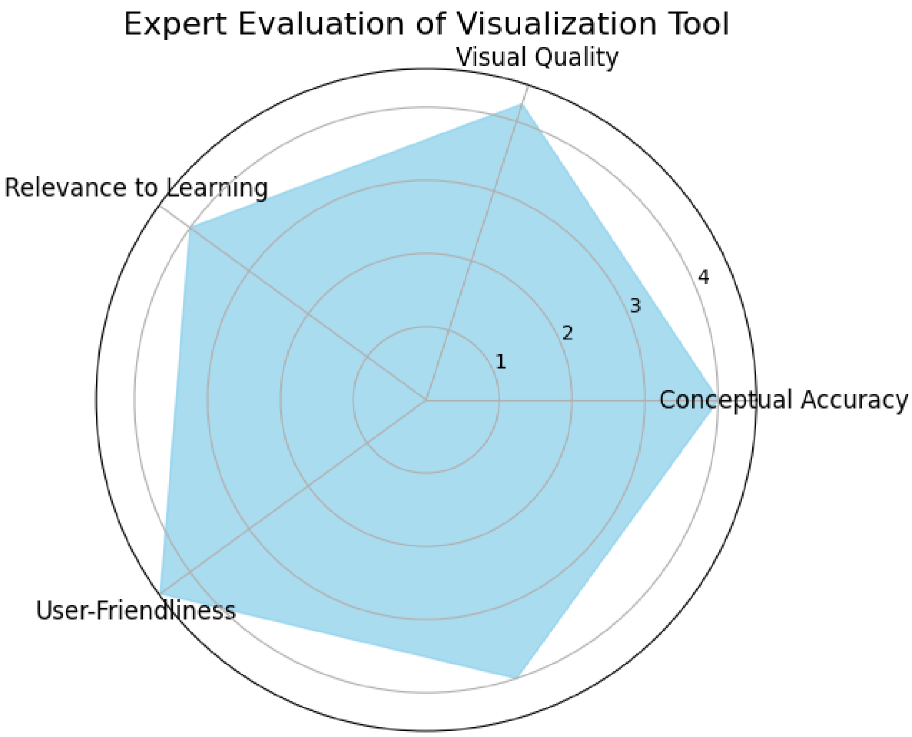

Figure 7. Results of Expert Evaluation of the Visualization Tool

The results of the expert evaluation of the mechanical properties visualization tool indicate highly positive outcomes. The accuracy of the tool's information is rated well, with an average score of 4, indicating that the tool is effective in conveying the concepts of mechanical material properties accurately. The quality of visualization received an excellent rating with an average score of 4.25, indicating that the visual representation of the tool falls within the category of good to very good. Additionally, the aspect of alignment with learning objectives received a relatively high rating with an average score of 4, suggesting good relevance in the context of learning, although there is a slight room for improvement. In terms of ease of use, the visualization tool received a very high rating with an average score of 4.5, reflecting that the tool is user-friendly. Overall, the expert evaluations provide a positive overview of the quality of the mechanical properties visualization tool, particularly in terms of information accuracy and user-friendliness. Despite minor areas for improvement in alignment with learning objectives, these positive assessment results indicate that the visualization tool can be relied upon as an effective learning resource in supporting the understanding of mechanical material properties concepts.

CONCLUSION

The design of a machine learning-based visualization tool integrated with the Streamlit framework can serve as an interactive learning medium in the era of digitalization. Based on the conducted research, it is evident that this tool can illustrate the cause-and-effect relationships of parameters influencing the changes in the mechanical properties of low-alloy steel. Each feature of this visualization tool can be utilized to support the analysis of mechanical properties and enhance students' understanding of material mechanical properties.

The expert evaluations of the visualization tool show an overall positive response. Aspects such as conceptual accuracy, visualization quality, alignment with learning objectives, and ease of use were rated as good to excellent by the experts. This visualization tool can be a valuable resource in supporting students' understanding of material mechanical properties, especially in the context of low-alloy steel. The tool's ability to integrate data from various sources, predict mechanical properties, and provide informative visual representations can enhance the effectiveness of learning. Although the research results indicate the success of this visualization tool, further research and development are still needed to test its effectiveness in various learning contexts and other material fields.

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