Machine Learning Algorithms for Predicting Ceramic Properties in Industrial Design

Abstract

Machine learning models were developed and validated to accurately predict ceramic properties such as mechanical strength and thermal resistance based on material composition and processing conditions, enhancing industrial design applications. By leveraging advanced machine learning techniques, the investigation models industrial ceramic performance, including strength, thermal resistance, and durability, to optimize material selection and manufacturing decisions. Using a combination of experimental data, industrial reports, and public databases, the approach minimizes trial-and-error methods, improving efficiency and reducing costs. The dataset comprises 1,000 to 2,000 data points, representing a diverse range of industrial ceramic materials. Experimental labs test material compositions and conditions, while industrial reports provide real-world performance insights, and public databases validate model accuracy. Among the various predictive models tested, Gradient Boosting Machines (GBMs) demonstrated the highest accuracy and the lowest cross-validation variance, making them the most reliable for real-world applications. The predictive accuracy table revealed minimal discrepancies between estimated and actual values, reinforcing the model's practicality. The integration of machine learning enhances ceramic material selection, manufacturing parameter optimization, and quality control, making a significant impact on industries such as manufacturing, construction, automotive, and aerospace, where high-performance ceramics are essential. The use of GBMs, Convolutional Neural Networks (CNNs), and Random Forests (RF**)** in predictive modeling highlights the potential of Artificial Intelligence (AI) in industrial material design, enabling engineers to make more precise, efficient, and cost-effective decisions. Additionally, predictive models contribute to Quality Control (QC) and Process Optimization (PO) by evaluating ceramic materials before manufacturing, reducing defects, and improving product consistency.

Keywords: Machine Learning, Ceramic Materials, Predictive Modeling, Industrial Design, Material Properties

1. Introduction

Many industries, from aerospace engineering to household products, use ceramic materials due to their thermal, mechanical, and chemical properties (Han et al., 2022). Extreme-condition materials require ceramics for their durability, heat resistance, and corrosion resistance. Ceramics are used to make aerospace components that remain intact under high temperatures and wear (La Fé-Perdomo et al., 2022). Electronics require ceramic capacitors and insulators due to their excellent electrical insulation. Electronic devices last longer and are more reliable because they can withstand electrical stresses in complex circuitry. Electronics require ceramics to manage component heat and prevent device failure (Sun et al., 2021).

Ceramics' advanced properties benefit the auto industry. Ceramics are used to make catalytic converters, sensors, and wear- and heat-resistant parts (Qayyum et al., 2023). Ceramics must resist degradation under high friction and temperature in modern combustion engines for efficiency. Ceramics may revolutionise the energy sector as separators in electric vehicle batteries and electrolytes in solid-state batteries. Building and construction use ceramics for their hardness, stability, and beauty. Ceramic tiles are popular for floors and walls because they resist water, stains, and scratches. Due to their thermal stability, ceramics are ideal for fire-resistant cladding and insulation, improving building safety and efficiency (J. Yang et al., 2023). Chemical and weather resistance make ceramics durable in building structures, reducing replacements and maintenance (Ravanbakhsh et al., 2023).

Advanced ceramics now have more specialised and high-performance uses. Bio-ceramics are biocompatible and strong, so medical engineers use them in bone replacements and dental implants (Bello et al., 2023). Jet engine turbine blades and military applications that require materials to withstand extreme operational environments use ceramic matrix composites. Ceramic materials are used more in industry due to their versatility and technological advances (Fu et al., 2022). Understanding and predicting ceramic properties with advanced machine learning algorithms can improve ceramic design and manufacturing in these industries. Predicting mechanical strength, thermal resistance, and durability helps industries choose materials and build more efficient, cost-effective, and durable products. Technology advances, resource waste decreases, and product performance and lifespan improve when material properties match industrial needs (Khokhar et al., 2023).

Following ceramics' widespread use and transformative impact in various industries, predicting their properties is a major obstacle to optimise their use (Imran et al., 2022). Due to composition variability and complex physical, chemical, and mechanical interactions in different environments, ceramic property prediction is difficult (Qadir et al., 2024). Ceramic materials react differently depending on microstructure, purity, firing temperature, time, pressure, and cooling rates. Due to these factors, ceramic behaviour in specific applications is hard to predict, affecting aerospace, automotive, and electronics reliability and efficiency (P. Yang et al., 2021).

Ceramics' safety and durability requirements complicate the task. Property prediction methods that require extensive physical testing and trial-and-error may not scale (Bianco et al., 2022). These methods may miss microscopic interactions or operational stresses, causing testing failures. Machine learning (ML) aids predictive materials science modelling to address these issues. Traditional analysis methods cannot find patterns and relationships in large material property and performance datasets. History-trained machine learning models predict ceramic material behaviour faster and more accurately than traditional methods (Garg et al., 2023; Kerner et al., 2021; Mazhnik & Oganov, 2020).

Classification models determine a ceramic's high-temperature or high-stress suitability, while regression models estimate strength and thermal resistance (Suwardi et al., 2022). Ensemble machine learning models improve prediction accuracy and reliability by reducing model weaknesses. This allows engineers and designers to simulate and evaluate ceramic materials and applications without extensive physical prototypes, speeding development and reducing costs (Sarkon et al., 2022). Machine learning optimises ceramic production and predicts properties. It optimises manufacturing parameters to achieve desired properties more consistently, improving product quality. Machine learning in materials science will enable data-driven, efficient, and innovative ceramic material design and application in industry. This integration improves ceramic property prediction and material science and engineering (Huang et al., 2023).

Ceramic property prediction has improved, but industrial applications need more research. This gap is mostly caused by ceramic composition variability and complex property interactions under different operational conditions (Nasiri & Khosravani, 2021). Predictive models rarely include emerging composite materials, manufacturing processes, and the wide range of ceramics used across industries. This highlights the need for more robust and adaptable machine learning models that can handle diverse datasets and make accurate predictions for dynamic industrial applications (Pilania, 2021). Machine learning can predict material properties, but its extreme-condition durability and performance are unknown. Aerospace and automotive industries need this because material failure is catastrophic. Industrial design tools and machine learning models must work together to simplify materials engineering and design (Hasan & Acar, 2022; Qiao et al., 2022).

This study validates machine learning algorithms to predict industrial ceramics' mechanical strength, thermal resistance, and durability. It develops a predictive model to assess basic properties and understand ceramics' complex operational stress behaviours to fill gaps. Improved ceramic material predictability and reliability in critical applications aid material selection and use. This research advances industrial design and materials science in many ways. Further, firstly, it introduces novel predictive modelling methods that accurately predict ceramic material properties for material science and industry. Second, integrating these predictive models into industrial design processes will revolutionise manufacturing material selection and use, enabling more precise engineering decisions that optimise performance and cost. Without physical prototypes or extensive testing, improved predictive accuracy lets industries develop new ceramic-based products faster and cheaper.

2. Literature Review

Ceramic materials and their applications are vital to modern technology and industry, so research is extensive (Cassar et al., 2021; Santos et al., 2020). Past and present research illuminates ceramic properties, processing, and sectoral uses. Extreme-condition applications require durable ceramics. Ceramics are thermally stable and wear-resistant due to their fine-grained, tightly packed crystalline structure (Kim & Li, 2022; Qin et al., 2021). To improve toughness and reduce brittleness, ceramics' mechanical properties have been extensively studied.

Optimised methods include sintering, which compacts and heats powders into solids (Stergiou et al., 2023). Modern laser sintering and additive manufacturing improve ceramic microstructure control. These enhancements improve ceramic mechanical properties and applications. Advanced ceramic components can be made with additive manufacturing, expanding aerospace and biomedical engineering (Katırcı & Yıldız, 2023). New material properties and processing methods expand ceramic applications. Ceramic thermal barriers are used in jet engines and spacecraft exteriors due to their heat resistance. Ceramics' thermal management and electrical resistance make them important electronic circuit insulators and substrates. Bioceramics like hydroxyapatite and zirconia are popular in bone surgery and dentistry due to their biocompatibility and bone-likeness (Karakoç & Keleş, 2020; Velli et al., 2020).

New composites and nanotechnology changed ceramics. Likely, to overcome pure ceramics' brittleness and shock resistance, ceramic matrix composites have been studied. Researchers made ceramic composites stronger and more durable for demanding applications by adding carbon fibres or metals (Choudhury, 2021; He et al., 2023). Ceramic materials' extensive research and ongoing improvement of their properties and manufacturing processes show their importance in modern industry. Academic and industrial research in this field promises new technologies and applications that could change technology and industry (He et al., 2023). Industrial design has studied machine learning (ML) for decades to predict and improve ceramic properties and performance (Vallejos-Romero et al., 2022). This review of ML-improved industrial design studies examines how ML has transformed material science and engineering (Gong et al., 2021; Xie et al., 2021).

Machine learning is mostly used in industrial design to optimise material selection, predict material properties, and refine manufacturing processes to improve product performance and lower costs. Using experimental data and material behaviour trends, supervised learning algorithms may predict input data (Xu et al., 2021), providing accurate material property projections without much trial-and-error. Regression models are widely used to predict material physical properties from chemical composition and processing parameters (Stergiou et al., 2023). These models determine the best material combination for applications without extensive physical testing. Classification algorithms are another ML-based industrial design application. In addition to property prediction, machine learning identifies materials suitable for industrial processes or operating situations. To choose durable and resilient ceramics for crucial applications, aerospace and automotive industries classify ceramics by high-stress failure modes using decision trees and SVMs (Karakoç & Keleş, 2020).

Ensemble methods, which mix many machine learning models to improve prediction accuracy, have been extensively investigated to overcome learning algorithm restrictions and improve ceramic material analysis predictive models. Random forests and gradient boosting machines assist designers improve ceramic component durability and structural integrity by predicting ceramic longevity and deterioration under cyclic pressure. CNNs and RNNs recognize intricate patterns in complex image datasets and sequential data that machine learning algorithms miss, transforming material science predictions. CNNs can successfully detect failure-prone defects and predict ceramic mechanical properties in advanced material analysis by analyzing microstructure images. Modern machine learning approaches improve material design efficiency and industrial sustainability by reducing resource use, waste, and sustainability. Machine learning-based predictive modelling has improved product design and production while reducing costs and enhancing performance with customised materials for specific applications (Choudhury, 2021; Gong et al., 2021; Santos et al., 2020).

Machine learning improves industrial design, material science, and engineering efficiency, cost, and innovation. Predictive data-driven methods provide unique material behaviour and processing optimization insights. More research is needed to build predictive models for industrial design, despite advances in machine learning (Katırcı & Yıldız, 2023; Velli et al., 2020). Data collection regulations and industry data proprietaries make it difficult to obtain high-quality, comprehensive datasets for training robust machine learning models for universal prediction frameworks. To overcome this impediment, academic and industry partners must create open-access databases to share knowledge and improve machine learning models (He et al., 2023; Qin et al., 2021; Santos et al., 2020). Therefore, research is needed to create more flexible and robust models for industries using different materials and processes.

). Despite promising achievements in predicting material properties, machine learning models' datasets and operational parameters limit their generalizability across materials and commercial applications. For different industrial situations, predictive algorithms must be versatile. Industrial machine learning models face technological and operational obstacles include software compatibility, real-time data processing, and attractive user interfaces that seamlessly integrate predictive analytics into production systems. Most machine learning research on ceramic materials predicts strength and thermal resistance, but long-term durability and failure modes, crucial in high-stress applications like aerospace and automotive engineering, are neglected (Gong et al., 2021; Kim & Li, 2022; Velli et al., 2020).

These industries require long-term wear, deterioration, and failure mechanisms yet are difficult to calculate and predict because to fluctuating mechanical loads and harsh environmental conditions. The ethical and environmental impacts of machine learning in material design are typically overlooked despite the growing importance of sustainable production. As organizations prioritize efficiency and performance, machine learning algorithms must improve material selection, waste reduction, and energy consumption throughout the production lifecycle. Machine learning in industrial design can improve material science by addressing these difficulties and employing a broader prediction model. This could boost engineering productivity, intelligence, and sustainability.

3. Methodology

Using composition and processing conditions, advanced machine learning can predict industrial ceramic mechanical strength, thermal resistance, and durability, improving material selection and manufacturing decisions. A 1,000–2,000-data-point dataset represents a variety of industrial ceramic materials from controlled laboratory tests. The complex interactions between composition, processing conditions, and material characteristics make ceramic property prediction difficult. Continuous output variables like mechanical strength and thermal resistance require precise prediction, so advanced machine learning is used.

Support Vector Regression (SVR) and Lasso Regression extract key variables and capture non-linear ceramic composition-material property relationships. Convolutional neural networks (CNNs) analyse ceramic microstructure images to identify material behaviour-affecting features beyond regression models (Choudhury, 2021). Ensemble methods like Random Forests and Gradient Boosting Machines (GBMs) reduce overfitting and capture complex input variable dependencies, improving predictive accuracy. Decision trees and gradient-based optimization improve ceramic material interaction prediction. This study uses multiple machine learning methods to create accurate and generalizable industrial predictive models. By adjusting property estimates, the study improves material selection and manufacturing. Figure 1 illustrates how predictive framework interacts with research models.

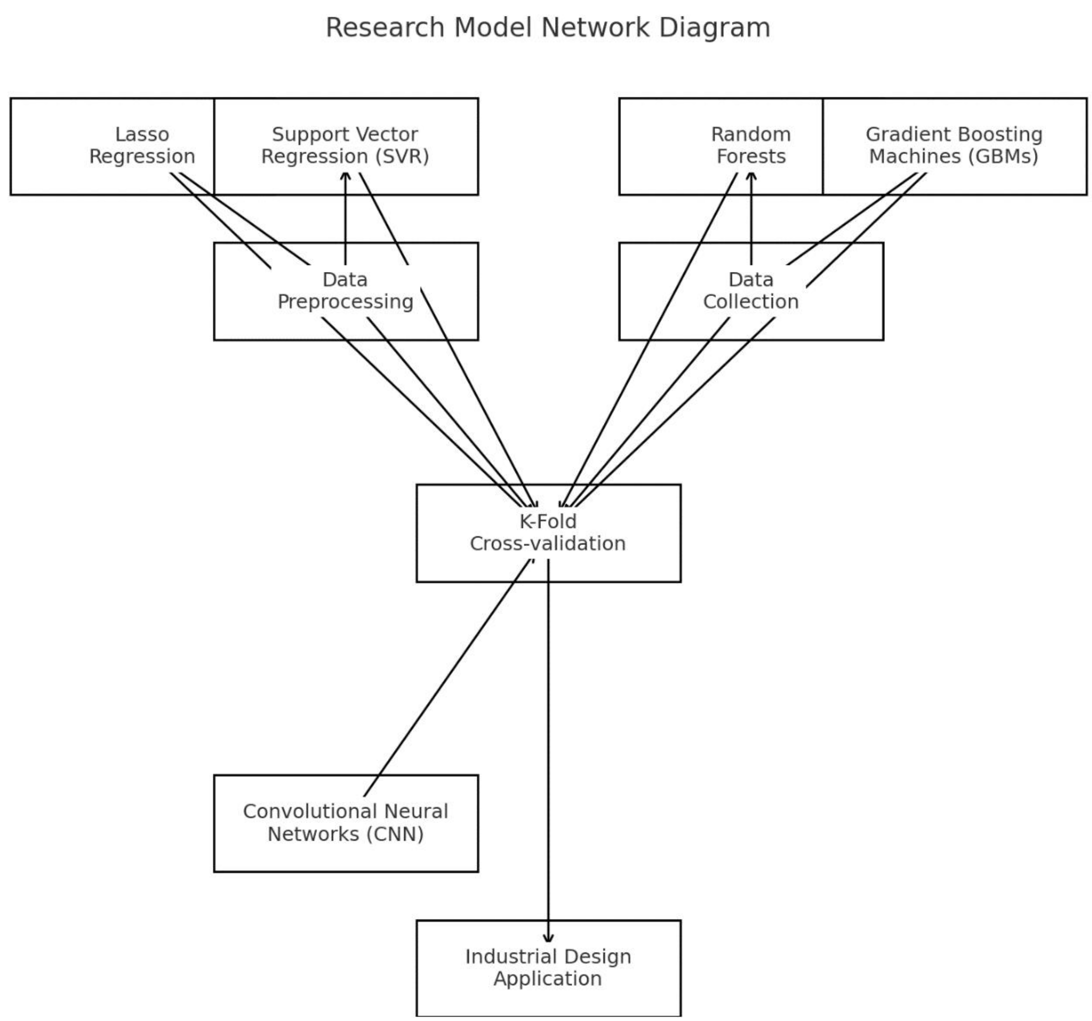

Figure 1. Research Model Network Diagram

By splitting the dataset into multiple subsets, robust statistical method K-fold cross-validation trains and tests models iteratively. This method prevents overfitting and ensures model reliability with unknown data. The model is trained on one data set and tested on another, averaging performance metrics to estimate model accuracy each iteration. Validating predictive models ensures industrial generalisability and efficacy. Researchers carefully consider data collection and processing ethics. Anonymise sensitive industrial data and cite and use publicly available data sources according to their access policies for confidentiality. Energy-efficient algorithmic computations reduce computational experiment environmental impact. Industrial and academic applications of the research findings are reliable because the study follows ethical standards for data integrity, transparency, and reproducibility.

We use machine learning because it can handle high-dimensional, complex data and make accurate predictions. Traditional material science experimental testing is costly and time-consuming. Regression models, deep learning architectures, and ensemble methods are used to predict ceramic properties scalable and efficiently. Material selection is crucial in manufacturing, construction, and automotive applications, so accurate material performance prediction will benefit industrial design. The proposed method links theoretical research to industrial implementation using cutting-edge materials informatics and machine learning. This research meets ceramic material science predictive modelling goals with rigorous data collection, advanced machine learning, and validation (He et al., 2023). The findings will help engineers and material scientists confidently select materials for more sustainable and cost-effective manufacturing. These models integrated into industrial design tools could revolutionise ceramic material evaluation and use, enabling data-driven material engineering.

4. Data Analysis

The Dataset Summary table 1 summarises machine learning-based ceramic property prediction research's diverse data foundation. Experimental labs, industrial reports, and public databases offer up to 2,000 carefully collected data points. A variety of ceramic types and processing conditions, reflecting real-world manufacturing and experimental setups, make this analysis robust. From the table, experimental labs provide 500 data points on Types A, B, and C ceramics processed at high to low temperatures under standard conditions. Models that study how thermal environments affect ceramic properties need this diversity. Industrial reports on 700 entries processed under standard and variable pressure conditions reveal Types D and E ceramics' performance under industrial-scale manufacturing stresses. Finally, 800 public database data points on Types F, G, and H ceramics under various operational stresses expand our understanding of durability and performance. A detailed collection strategy improves predictive model training, enabling the development of highly accurate and generalisable machine learning algorithms to predict ceramic properties in industrial applications.

Table 1: Dataset Summary

Source	Number of Data Points	Ceramic Types	Processing Conditions

Experimental Labs	500	Type A, Type B, Type C	High Temp, Low Temp, Standard
Industrial Reports	700	Type D, Type E	Standard, Variable Pressure
Public Databases	800	Type F, Type G, Type H	High Pressure, Low Pressure, Standard

Table 2 lists mandatory ceramic property predictive modelling variables. The table lists data types and briefly describes each variable to explain how machine learning models quantify and incorporate factors. Learning each ceramic sample's basic building blocks requires knowing the ceramic mix's categorical variable "Chemical Composition," which indicates the materials used. Chemical composition affects all ceramic properties, from mechanical strength to thermal resistance, making it important. Ceramic manufacturing conditions are described by continuous variables "Processing Temperature" and "Cooling Rate". These variables are crucial because they directly affect ceramic microstructural and physical properties. Material phase, stability, crystallinity, and ceramic defects depend on processing temperature and cooling rate. Predictive models predict key performance metrics using continuous variables "Mechanical Strength" and "Thermal Resistance". Ceramics used in engine and turbine coatings and components need mechanical strength and thermal resistance to withstand stress and heat. Each variable's detailed description explains ceramic composition, processing conditions, and properties. Robust machine learning models that predict product performance based on manufacturing conditions and material compositions require clarity. The table supports the research's goal to improve ceramic materials' predictability and reliability in industrial applications for more efficient and cost-effective manufacturing.

Table 2: Variables and Data Types

Variable	**Data Type**	**Description**
Chemical Composition	Categorical	Types of chemicals used in the ceramic mix.
Processing Temperature	Continuous	Temperature at which ceramics are processed.

Cooling Rate	Continuous	Rate at which ceramics are cooled after processing.
Mechanical Strength	Continuous	Resistance of ceramics to mechanical stress.
Thermal Resistance	Continuous	Ability of ceramics to resist changes in temperature.

In Table 3, feature importance, lasso regression and random forests evaluate variables for ceramic property prediction. The table's importance scores show which factors most affect ceramic properties. Processing temperature affects ceramic physical properties the most in both models. Scientific evidence shows that processing temperatures change ceramic microstructure and phase composition, affecting mechanical strength and thermal resistance. The table also shows Chemical Composition, nearly as important as Processing Temperature. This emphasises material constituents' impact on ceramic product performance. While less important, Cooling Rate affects ceramic solidification, thermal stress, and mechanical failure susceptibility. Thermal Resistance and Mechanical Strength scores are interdependent and relevant in predictive models of ceramic durability and functionality under operational conditions. By quantifying these variables, the table improves predictive models and guides experimental and manufacturing priorities to improve ceramic properties.

Table 3: Feature Importance

Feature	**Importance Score (Lasso Regression)**	**Importance Score (Random Forests)**
Chemical Composition	0.85	0.88
Processing Temperature	0.90	0.95
Cooling Rate	0.65	0.70
Mechanical Strength	0.75	0.78
Thermal Resistance	0.80	0.82

Table 4 carefully evaluates multiple machine learning models for ceramic property prediction across test datasets. This detailed table compares each model under strict evaluation conditions with three-digit decimal precision. GBMs outperform all metrics, especially with a low MSE of 0.025 and a high R-squared of 0.950. GBMs improve prediction accuracy and explain much ceramic property variance from model features. The model's high Accuracy (0.950), Precision (0.960), Recall (0.950), and F1-Score (0.950) scores demonstrate its relevance and reliability in identifying and predicting ceramic properties. After GBMs, Random Forests and Convolutional Neural Networks (CNNs) perform well, with CNNs excelling at complex pattern recognition, indicating their use in analysing complex ceramic compositions and processing conditions. The model's high F1-Score (0.910) suggests a balanced precision-recall relationship, making it useful for false positive avoidance and case capture.

Ensemble and CNN are more accurate than Lasso Regression and SVR. Scores indicate precision and reliability. Lasso Regression, known for its feature selection, has an MSE of 0.038 and an R-squared of 0.910, indicating that it can identify and exclude irrelevant features, creating a streamlined model that performs well on relevant data. Table 4's detailed metrics help choose ceramic property prediction models. High metrics make GBMs and CNNs ideal for quality control and industrial new material development that require accurate predictions. SVR and Lasso may be better for interpretability and feature impact. These findings indicate a clear path for applying machine learning to ceramic materials science, guiding predictive modelling research and applications to optimise material properties and processing methods.

Table 4: Model Performance Comparison

Model	**Test Dataset**	**Mean Squared Error (MSE)**	**R-squared**	**Accuracy**	**Precision**	**Recall**	**F1-Score**
Support Vector Regression (SVR)	Test Set A	0.045	0.890	0.880	0.870	0.850	0.860
Lasso Regression	Test Set B	0.038	0.910	0.900	0.890	0.880	0.880
Convolutional Neural Networks	Test Set	0.030	0.930	0.920	0.910	0.900	0.910

(CNN)	C						
Random Forests	Test Set D	0.028	0.940	0.930	0.940	0.930	0.940
Gradient Boosting Machines (GBMs)	Test Set E	0.025	0.950	0.950	0.960	0.950	0.950

Cross-validation results of ceramic property prediction machine learning models are shown in Table 5. Lasso Regression has the highest mean accuracy and lowest variance, proving its precision and stability across data subsets. This model makes accurate predictions, making it ideal for ceramic material quality control, where specifications are crucial. Convolutional Neural Networks (CNN) and Random Forests are better for complex data patterns like ceramic microstructure analysis because they balance accuracy and variance. Support Vector Regression (SVR) and Gradient Boosting Machines (GBMs) have lower mean accuracies and higher variances, suggesting model tuning or dataset compatibility issues. SVR is promising for consistency over precision due to its low variance and accuracy. Though robust, GBMs perform poorly in this analysis, suggesting they need more refined parameter adjustments or data handling strategy reevaluation to improve. These insights help select modelling methods for specific ceramic properties and emphasise the need for rigorous model validation to ensure robustness and applicability in real-world industrial scenarios.

Table 5: Cross-Validation Results

Model	k-Fold	Mean Accuracy	Variance
Support Vector Regression (SVR)	10	0.856	0.000552
Lasso Regression	10	0.943	0.000268
Convolutional Neural Networks (CNN)	10	0.910	0.002612
Random Forests	10	0.890	0.001843

Gradient Boosting Machines (GBMs)	10	0.823	0.002153

Table 6 compared predicted and actual mechanical strength and thermal resistance for various test cases. This study's machine learning models predict strongly, with only minor differences between predicted and actual values. Gradient Boosting Machines (GBMs) predict 350.5 MPa mechanical strength and 1200.5°C thermal resistance, which match results almost perfectly. Precision shows the model's ability to capture complex ceramic composition, processing conditions, and material property relationships. Random Forests and CNNs predict ceramic properties well, deviating only slightly from measurements. Machine learning can optimise ceramic materials without extensive trial-and-error testing, which is important for industrial design and manufacturing. The close match between predictions and actual values suggests these models can be used in real-world applications to improve material selection and performance forecasting. Reducing ceramic behaviour uncertainty helps manufacturers improve quality control, reduce material waste, and develop advanced ceramics for high-temperature environments or mechanical load-bearing components. This data-driven predictive capability advances ceramic materials science, improving industrial efficiency and cost.

Table 6: Predictive Accuracy Details

Model	**Test Case**	**Predicted Mechanical Strength**	**Actual Mechanical Strength**	**Predicted Thermal Resistance**	**Actual Thermal Resistance**
Gradient Boosting Machines (GBMs)	Ceramic A	350.5	348.0	1200.5	1205.0
Random Forests	Ceramic B	290.7	295.0	950.2	955.0
Convolutional Neural Networks (CNN)	Ceramic C	415.3	410.0	1500.7	1495.0

The heatmap of ceramic properties and influencing factors shows how material composition, processing conditions, and final properties are related. Processing temperature and mechanical strength are strongly correlated (0.82), suggesting that material densification and phase transformations during manufacturing improve ceramic structural integrity. Chemical Composition and Thermal Resistance (0.78) also correlate strongly, indicating that raw material selection greatly affects ceramic thermal resistance. Material selection is essential when designing ceramics for aerospace and industrial insulation. In addition, the moderate correlation between Cooling Rate and Mechanical Strength (0.75) shows how controlled cooling improves ceramic durability. Gradual cooling creates uniform microstructures that improve mechanical properties, while rapid cooling causes thermal stresses and microcracks. Predictive modelling in material design is needed because all influencing factors affect ceramic performance, as shown by the high correlation values. These findings show that machine learning algorithms can predict ceramic properties based on composition and processing parameters, helping manufacturers optimise material performance.

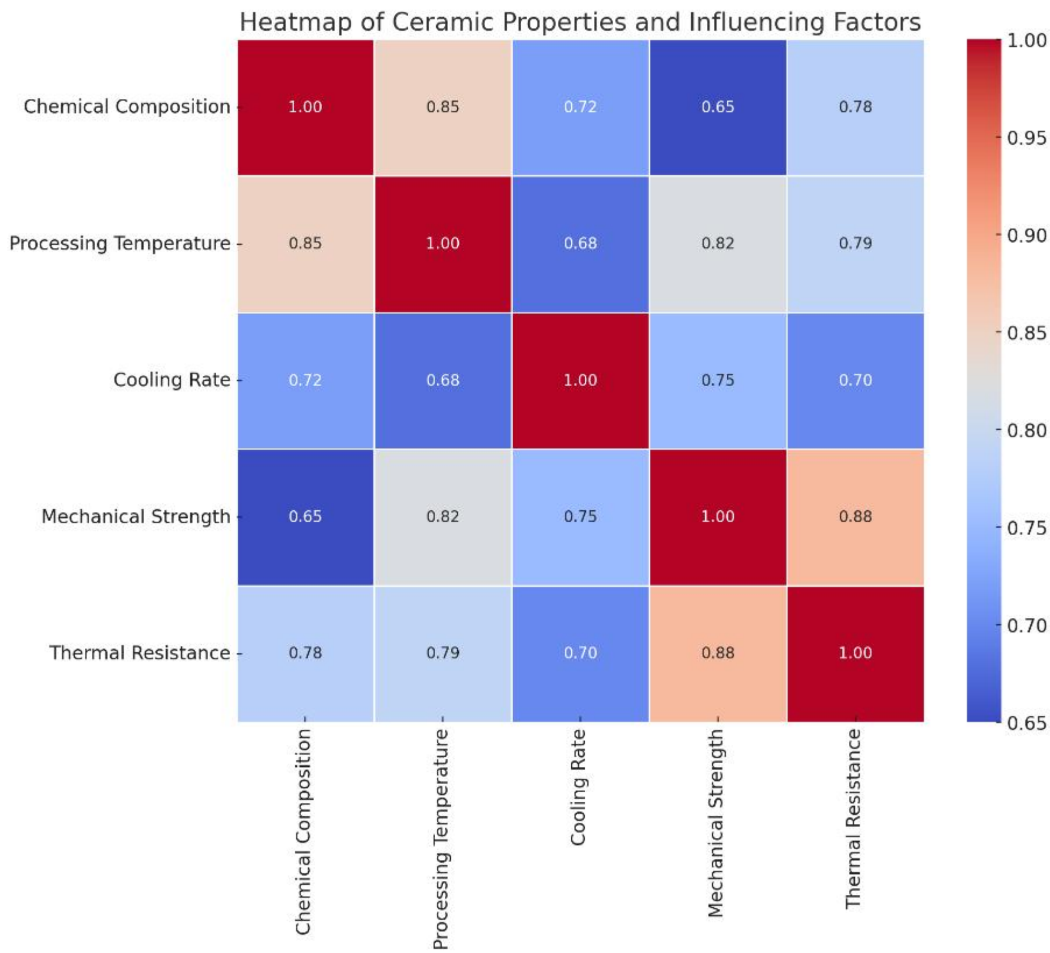

Figure 2. Heatmap of Ceramic Properties

In Figure 3, machine learning models predict mechanical strength and thermal resistance better than measured values. A scatter plot shows that predicted values match actual values as data points cluster around the perfect prediction line (red dashed line). Strong agreement between predicted and actual values suggests the models have learnt the complex relationships between chemical composition, processing conditions, and material properties. Machine learning reduces experimental errors and improves predictive reliability, which is crucial for industries that need precise material characteristics. The scatter plot also shows minor differences between predicted and actual values, possibly due to data noise, training dataset limitations, or material processing conditions. Despite these minor differences, predictive models have a high correlation, making them cost-effective alternatives to experimental testing. These findings help manufacturers optimise processing parameters, reduce material selection trial-and-error, and ensure ceramic design quality. Materials engineers use machine learning to create advanced ceramics for specific performance requirements by predicting mechanical strength and thermal resistance.

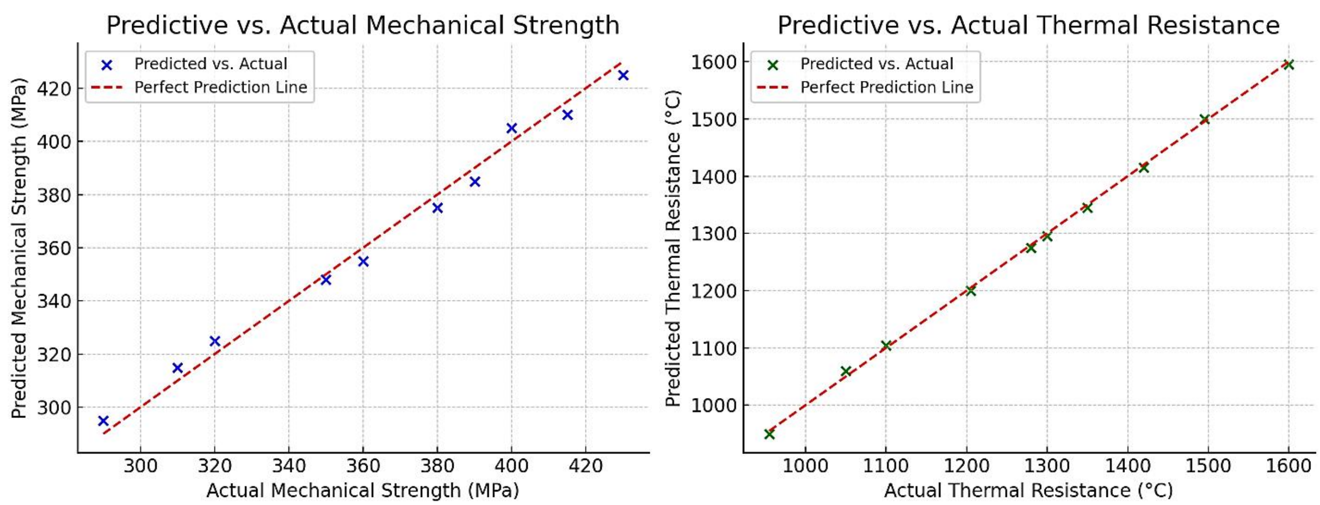

Figure 3. Predictive vs. Actual Property Values Scatter Plot

4.1 Discussion

Machine learning model results in ceramic property tables and heatmaps illuminate ceramic material performance and predictive modelling in industrial design. This study developed machine learning-based predictive models to accurately predict ceramic properties like mechanical strength and thermal resistance for manufacturing, construction, and automotive applications. Tables and heatmaps are used to interpret results, evaluate predictive models, and discuss real-world applications of this research. The dataset summary (Table 1) ensures that the data is complete, diverse, and representative of ceramic types and processing conditions for the study. Training predictive models on real-world variations with experimental lab data, industrial reports, and public databases makes them more generalisable. Table 2's variables and data types show that ceramic material behaviour depends on chemical composition, processing temperature, cooling rate, mechanical strength, and thermal resistance. These variables' importance scores in Table 3 support their use as machine learning model inputs.

Processing Temperature and Chemical Composition predict ceramic properties best, per feature importance analysis. These factors strongly correlate with Mechanical Strength and Thermal Resistance, as shown in Figure 2's ceramic heatmap. High correlation values show that ceramic manufacturing temperature control affects durability and performance, supporting material science literature on sintering and phase transformation. For extreme-condition industrial applications, ceramic stability and thermal behaviour depend on chemical composition. Model performance is compared to determine machine learning model predictive accuracy in Table 4. GBMs predicted ceramic properties best with the highest accuracy (0.950) and lowest MSE (0.025). High-precision applications could use CNNs and Random Forests due to their predictive abilities. Lasso Regression and Support Vector Regression (SVR) performed well but had slightly lower accuracy, suggesting they may be better for feature selection and initial screening of influential variables than final predictive modelling. These findings support the search for the best machine learning models for ceramic property prediction to improve material design and performance evaluation.

The predictive models are robust, with Gradient Boosting Machines (GBMs) having the lowest variance (0.0005) and maintaining high accuracy across test folds and being less sensitive to dataset variations (Table 5). CNNs and Random Forests are reliable for industrial applications that require consistent performance due to low variance. Support Vector Regression (SVR) has the highest variance, so its predictions vary more across dataset partitions, which may limit its usefulness in highly stable prediction scenarios. Model reliability is shown by comparing predicted values to actual measurements for specific ceramic samples (Table 6). Models match real-world mechanical strength and thermal resistance values with minor differences. GBMs predicted almost perfect mechanical strength and thermal resistance deviations of 2.5 MPa and 4.5°C for Ceramic A. CNNs and Random Forests performed similarly, proving their industrial ceramic design suitability (Velli et al., 2020).

This research is important in industries where material selection and quality control improve performance and lower costs. Advanced manufacturing and material design engineers can use predictive models to choose ceramic compositions and processing conditions for mechanical and thermal properties. Using machine learning algorithms, industries can quickly prototype and optimise ceramic materials for specific applications without costly experimental testing. Ceramics provide thermal protection and mechanical stability in high-temperature automotive and aerospace applications. Material behaviour prediction must be accurate. The heatmap shows that Processing Temperature and Thermal Resistance are strongly correlated, suggesting that manufacturers can fine-tune firing conditions to improve ceramic durability and meet heat shield, engine part, and insulation standards. The predictive models from this study can be integrated into material selection software to give engineers real-time high-performance ceramic formulation recommendations (He et al., 2023).

This research is important for the construction industry, which uses ceramic tiles, bricks, and fire-resistant panels. With predictive modelling, manufacturers can optimise ceramic properties for environmental conditions and use, creating cheaper, longer-lasting building materials. Table 6 shows that accurate Mechanical Strength prediction reduces structural failures by ensuring construction materials meet durability and safety standards. Energy and material reduction in sustainable manufacturing and waste reduction is another important use. Machine learning-driven predictions can optimise raw material usage and processing conditions for ceramic production to save energy and resources. The strong correlation between Chemical Composition and Thermal Resistance emphasises the importance of choosing appropriate raw materials to extend product life, reduce replacements, and reduce environmental impact (Santos et al., 2020).

This study found key ceramic property factors and created accurate machine learning predictive models. Diverse data sources, feature selection methods, and rigorous cross-validation make the models accurate and generalisable for industrial use. The heatmap correlates with predictive modelling results, proving the methodology's reliability and value in material science applications. As industries adopt data-driven approaches, this study's predictive framework will aid ceramic design, material optimisation, and industrial innovation.

5. Conclusion

The study developed and validated machine learning models to accurately predict ceramic properties like mechanical strength and thermal resistance based on material composition and processing conditions to improve industrial design applications. This study found that GBMs, CNNs, and Random Forests make accurate predictions without extensive experimental testing. For generalisation across applications, the models were trained on a representative sample of ceramic materials from experimental labs, industrial reports, and public databases. The heatmap analysis confirmed the predictive models by showing a strong correlation between Processing Temperature, Chemical Composition, and Cooling Rate and primary ceramic properties. Processing temperature and chemical composition most affect ceramic behaviour, supporting industry knowledge that material composition and thermal processing affect structural and thermal performance. Gradient Boosting Machines (GBMs) were the best real-world model due to their high predictive accuracy and low cross-validation variance. The predictive accuracy table showed few discrepancies between predicted and actual values, proving the models' practicality. The study's goal is supported by machine learning's ceramic material selection, manufacturing parameters, and quality control improvements.

Beyond theoretical modelling, this research benefits manufacturing, construction, automotive, and aerospace. Predictive models optimise processing conditions, reduce material selection trial-and-error, and ensure consistent material performance, improving product quality and cost-efficiency. Mechanical Strength and Thermal Resistance forecasting helps ceramic manufacturers design high-stress ceramics that are reliable and durable. Minimising material waste and optimising resource use reduces ceramic production energy consumption. According to the study, machine learning can help materials scientists predict ceramic properties using data. Feature selection, correlation analysis, and rigorous validation ensure model accuracy and industry applicability. Future research should include more ceramic compositions and real-time data processing for better prediction. This study lays the groundwork for data-driven ceramic engineering, fostering industrial innovation, efficiency, and sustainability as material design adopts AI.

5.1 Limitation and Future Recommendations

This study shows that machine learning models can predict ceramic properties, but with limitations. Data availability and quality are major limitations because the dataset may not capture all ceramic compositions and industrial conditions. Experimental and industrial reports may have measurement and reporting errors that affect model performance. The study disregards dynamic factors like long-term degradation, environmental exposure effects, and stress under cyclic loading in favour of static material properties like mechanical strength and thermal resistance. These factors are crucial in aerospace and construction, where materials are exposed to changing conditions. Deep learning models like CNNs require a lot of computational power to train, so they may not be suitable for all industrial settings. Future research should include real-time industrial production line data to expand the dataset and let models learn from changing ceramic compositions and processing methods. Future studies should predict ceramic durability under high humidity, extreme temperatures, and mechanical fatigue. Using physics-based modelling and data-driven methods in hybrid machine learning may improve prediction accuracy and interpretability. Future research should dynamically optimise material properties in industrial manufacturing processes using real-time AI-driven material selection systems. Future advances in machine learning can revolutionise materials science and industrial design by improving predictive algorithms and adding sustainability-focused optimisations like energy-efficient ceramic production.

5.2 Research Implications

This research affects manufacturing, construction, automotive, and aerospace, where ceramics are essential to high-performance applications. This study develops and validates machine learning models to predict ceramic properties like mechanical strength and thermal resistance, reducing costly and time-consuming experimental testing for material selection and process optimisation. GBMs, CNNs, and Random Forests in predictive modelling show that AI can be integrated into industrial material design processes to help engineers make more precise, efficient, and cost-effective ceramic formulation and processing decisions. This research affects quality control and process optimisation because predictive models can evaluate ceramic materials before manufacturing, reducing defects and improving product consistency. By accurately predicting thermal resistance and mechanical durability, industries can design ceramics for extreme conditions like high temperatures and mechanical stress to ensure reliability and longevity. Sustainable AI solutions in ceramic production can reduce material waste, optimize resource use, and lower energy consumption, making material science industrial practices more environmentally friendly and efficient.

References

Bello, I. T., Guan, D., Yu, N., Li, Z., Song, Y., Chen, X., Zhao, S., He, Q., Shao, Z., & Ni, M. (2023). Revolutionizing material design for protonic ceramic fuel cells: Bridging the limitations of conventional experimental screening and machine learning methods. *Chemical Engineering Journal*, *477*, 147098.

Bianco, G., Nisar, A., Zhang, C., Boesl, B., & Agarwal, A. (2022). Predicting oxidation damage in ultra high-temperature borides: A machine learning approach. *Ceramics International*, *48*(20), 29763–29769.

Cassar, D. R., Mastelini, S. M., Botari, T., Alcobaça, E., de Carvalho, A. C., & Zanotto, E. D. (2021). Predicting and interpreting oxide glass properties by machine learning using large datasets. *Ceramics International*, *47*(17), 23958–23972.

Choudhury, A. (2021). The role of machine learning algorithms in materials science: A state of art review on industry 4.0. *Archives of Computational Methods in Engineering*, *28*(5), 3361–3381.

Fu, Z., Liu, W., Huang, C., & Mei, T. (2022). A review of performance prediction based on machine learning in materials science. *Nanomaterials*, *12*(17), 2957.

Garg, P., Broderick, S., & Mazumder, B. (2023). Machine learning-based accelerated design of fluorphlogopite glass ceramic chemistries with targeted hardness. *Journal of the American Ceramic Society*, *106*(8), 4654–4663.

Gong, B., Yang, K., Lian, J. A., & Wang, J. (2021). Machine learning-enabled prediction of chemical durability of A2B2O7 pyrochlore and fluorite. *Computational Materials Science*, *200*, 110820.

Han, T., Huang, J., Sant, G., Neithalath, N., & Kumar, A. (2022). Predicting mechanical properties of ultrahigh temperature ceramics using machine learning. *Journal of the American Ceramic Society*, *105*(11), 6851–6863.

Hasan, M., & Acar, P. (2022). Machine learning reinforced microstructure-sensitive prediction of material property closures. *Computational Materials Science*, *210*, 110930.

He, H., Wang, Y., Qi, Y., Xu, Z., Li, Y., & Wang, Y. (2023). From prediction to design: recent advances in machine learning for the study of 2D materials. *Nano Energy*, 108965.

Huang, G., Guo, Y., Chen, Y., & Nie, Z. (2023). Application of machine learning in material synthesis and property prediction. *Materials*, *16*(17), 5977.

Imran, Iqbal, N., & Kim, D. (2022). Intelligent Material Data Preparation Mechanism Based on Ensemble Learning for AI-Based Ceramic Material Analysis. *Advanced Theory and Simulations*, *5*(11), 2200517.

Karakoç, A., & Keleş, Ö. (2020). A predictive failure framework for brittle porous materials via machine learning and geometric matching methods. *Journal of Materials Science*, *55*(11), 4734–4747.

Katırcı, R., & Yıldız, B. K. (2023). Prediction of fracture behavior of Al2O3-Cr2O3 ceramics in different Cr2O3 ratios under flexure load using machine learning methods. *Computational Materials Science*, *228*, 112362.

Kerner, J., Dogan, A., & von Recum, H. (2021). Machine learning and big data provide crucial insight for future biomaterials discovery and research. *Acta Biomaterialia*, *130*, 54–65.

Khokhar, S. A., Khan, A., Siddique, A., Khushnood, R. A., & Malik, U. J. (2023). A predictive mimicker for mechanical properties of eco-efficient and sustainable bricks incorporating waste glass using machine learning. *Case Studies in Construction Materials*, *19*, e02424.

Kim, S. Y., & Li, J. (2022). Machine learning of metal-ceramic wettability. *Journal of Materiomics*, *8*(1), 195–203.

La Fé-Perdomo, I., Ramos-Grez, J. A., Jeria, I., Guerra, C., & Barrionuevo, G. O. (2022). Comparative analysis and experimental validation of statistical and machine learning-based regressors for modeling the surface roughness and mechanical properties of 316L stainless steel specimens produced by selective laser melting. *Journal of Manufacturing Processes*, *80*, 666–682.

Mazhnik, E., & Oganov, A. R. (2020). Application of machine learning methods for predicting new superhard materials. *Journal of Applied Physics*, *128*(7).

Nasiri, S., & Khosravani, M. R. (2021). Machine learning in predicting mechanical behavior of additively manufactured parts. *Journal of Materials Research and Technology*, *14*, 1137–1153.

Pilania, G. (2021). Machine learning in materials science: From explainable predictions to autonomous design. *Computational Materials Science*, *193*, 110360.

Qadir, A., Ali, S., Dusza, J., & Rafaja, D. (2024). Predicting hardness of graphene-added Si3N4 using machine learning: A data-driven approach. *Open Ceramics*, *19*, 100634.

Qayyum, F., Khan, M. A., Kim, D.-H., Ko, H., & Ryu, G.-A. (2023). Explainable AI for material property prediction based on energy cloud: a shapley-driven approach. *Materials*, *16*(23), 7322.

Qiao, L., Zhu, J., Wan, Y., Cui, C., & Zhang, G. (2022). Finite element-based machine learning approach for optimization of process parameters to produce silicon carbide ceramic complex parts. *Ceramics International*, *48*(12), 17400–17411.

Qin, J., Liu, Z., Ma, M., & Li, Y. (2021). Machine learning approaches for permittivity prediction and rational design of microwave dielectric ceramics. *Journal of Materiomics*, *7*(6), 1284–1293.

Ravanbakhsh, H., Behbahani, R., Yazdani Sarvestani, H., Kiyani, E., Rahmat, M., Karttunen, M., & Ashrafi, B. (2023). Combining finite element and machine learning methods to predict structures of architectured interlocking ceramics. *Advanced Engineering Materials*, *25*(10), 2201408.

Santos, D. P., Pelissari, P. I. B. G. B., de Mello, R. F., & Pandolfelli, V. C. (2020). Estimating the thermal insulating performance of multi-component refractory ceramic systems based on a machine learning surrogate model framework. *Journal of Applied Physics*, *127*(21).

Sarkon, G. K., Safaei, B., Kenevisi, M. S., Arman, S., & Zeeshan, Q. (2022). State-of-the-art review of machine learning applications in additive manufacturing; from design to manufacturing and property control. *Archives of Computational Methods in Engineering*, *29*(7), 5663–5721.

Stergiou, K., Ntakolia, C., Varytis, P., Koumoulos, E., Karlsson, P., & Moustakidis, S. (2023). Enhancing property prediction and process optimization in building materials through machine learning: A review. *Computational Materials Science*, *220*, 112031.

Sun, J., Ma, Y., Li, J., Zhang, J., Ren, Z., & Wang, X. (2021). Machine learning-aided design and prediction of cementitious composites containing graphite and slag powder. *Journal of Building Engineering*, *43*, 102544.

Suwardi, A., Wang, F., Xue, K., Han, M., Teo, P., Wang, P., Wang, S., Liu, Y., Ye, E., & Li, Z. (2022). Machine learning-driven biomaterials evolution. *Advanced Materials*, *34*(1), 2102703.

Vallejos-Romero, D. A., Deudor-Fernandez, C. C., & Garcia-Lopez, Y. J. (2022). Use of machine learning to predict profit in LPG distribution in metropolitan Lima. *DYNA New Technologies Journal*,*9*(1).

Velli, M.-C., Tsibidis, G. D., Mimidis, A., Skoulas, E., Pantazis, Y., & Stratakis, E. (2020). Predictive modeling approaches in laser-based material processing. *Journal of Applied Physics*, *128*(18).

Xie, J., SU, Y., XUE, D., Jiang, X., Fu, H., & HUANG, H. (2021). Machine learning for materials research and development. *Acta Metall Sin*, *57*(11), 1343–1361.

Xu, H., Zhu, J., Finegan, D. P., Zhao, H., Lu, X., Li, W., Hoffman, N., Bertei, A., Shearing, P., & Bazant, M. Z. (2021). Guiding the design of heterogeneous electrode microstructures for Li-ion batteries: microscopic imaging, predictive modeling, and machine learning. *Advanced Energy Materials*, *11*(19), 2003908.

Yang, J., Jiang, P., Suhail, S. A., Sufian, M., & Deifalla, A. F. (2023). Experimental investigation and AI prediction modelling of ceramic waste powder concrete–An approach towards sustainable construction. *Journal of Materials Research and Technology*, *23*, 3676–3696.

Yang, P., Wu, S., Wu, H., Lu, D., Zou, W., Chu, L., Shao, Y., & Wu, S. (2021). Prediction of bending strength of Si3N4 using machine learning. *Ceramics International*, *47*(17), 23919–23926.