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PREDICTING ALUMINA COMPOSITES' MECHANICAL CHARACTERISTICS USING A MACHINE LEARNING APPROACH

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A B S T R A C T

Obtaining the requisite properties in alloys is crucial problem in the production of aluminium components, requiring great deal of time and effort for investigation and experimentation. In this study, machine-learning technique utilizing Bayesian-fine tuned Adaptive Gated Recurrent Unit (B-AGRU) to forecast the mechanical characteristics of aluminium alloys is presented. Training and testing are conducted on dataset, which has undergone comprehensive preparation process that includes cleaning and Z-score normalization. Principal Component Analysis (PCA) is used for feature extraction to increase algorithmic efficiency. The GRU approach, which is implemented in Python, hardness and yield strength, leading in more accurate findings. When compared to standard methodologies, process saves significant time and energy, as evidenced by metrics such as RMSE-20%, MAE-10% and R-squared-97%. This study reveals B-AGRU-based machine learning as a feasible strategy for enhancing efficiency and sustainability in forecasting mechanical properties of aluminium alloys, paving the way for wider application in industrial sector.

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1. INTRODUCTION

In the field of sophisticated materials, alumina composites stand out as a collection of substances with excellent mechanical properties, making them useful in industries ranging from aerospace to biomedical engineering (Raju et al., (2020)). Because of their unique combination of strength, hardness and thermal stability, these aluminum oxide (Al2O3) composites are suitable for a wide range of applications (Agrawal and Satapathy (2019)). Understanding and anticipating alumina composite mechanical characteristics is crucial for optimizing their performance in a wide range of applications, from spacecraft structural components to cutting-edge medical implants (Boopalakrishnan et al., (2023)).

The backbone of these composites is alumina, which is known for its hardness and wear resistance. It is the deliberate incorporation of other elements, typically in the form of reinforcing phases or additives that unlocks the full potential of alumina composites. Secondary

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phases can contain ceramics, polymers, or even metallic components, each of which provides unique properties to the resulting composite material (Kota et al., (2022)). The interaction of the main alumina matrix with various additives yields a material with customized properties, allowing engineers to construct materials with specified performance features (Lakhdar et al., (2021)).

Alumina composites' physical properties are multifaceted, encompassing a range of characteristics including tensile strength, hardness, fracture toughness and fatigue resistance. To learn the possibilities of these materials, researchers and engineers use predictive models that account for a variety of factors influencing the physical properties of the composites (Goswami et al., (2022)). There is a complex interplay between the composition, processing methods and microstructure of alumina composites, as these factors have a significant impact on their mechanical responses (Cygan et al., (2019)).

Predicting mechanical properties is essential for guaranteeing the dependability and safety of components composed of alumina composites along with optimizing material efficiency (Sharma et al., (2022)). In mission-critical situations, accurate prediction of the mechanical characteristics of aluminium composite might be the distinction between success and disaster, such as in aircraft applications where weight, strength and thermal stability are essential elements (Altıparmak et al., (2022)). Analogously, in the biomedical domain, predicting the mechanical characteristics of alumina composites is critical to the design of implants that can endure the physiological stresses imposed by the human body (Palmero (2019)).

Banerjee et al., (2020) utilized an artificial intelligence-driven approach, utilizing artificial neural networks (ANN) and genetic algorithms, to optimize the composition size; based on conflicting goal functions generated from literature data, they investigated the mechanical and morphological features of alumina-reinforced composites made of aluminum matrix for better tribo-mechanical properties. The technique produces Pareto solutions for customized composite design, with findings proving improved performance while accepting study constraints.

Liu et al., (2022) predicted the mechanical characteristics of graphene-reinforced aluminum nanocomposites by combining molecular dynamics simulations with machine learning (ML) approaches. Incorporating graphene volume fractions, alignment angle, chirality along with the temperature into MD simulations results in the development of ML models for Young's modulus and ultimate tensile strength, as well as the modification of the Halpin-Tsai model for enhanced Young's modulus accuracy in forecasting, allow for more practical assessment and development of graphene-aluminum nanocomposite material structures.

Najjar et al., (2022) used a micromechanics model and finite element simulation to estimate elastic modulus in Cu-Al2O3 nanocomposites utilizing a rule of mixing and grain evolution. Using "finite element (FE)" outputs and experimental data, a Random vector functional link network machine learning model was developed, attaining a high R¬2 (0.99) for predicting yield strength in micro indentation tests on produced nanocomposites. The technique effectively combines modeling, simulation & machine learning to forecast mechanical parameters with excellent agreement with data from experiments.

Yu et al., (2021) predicted the mechanical characteristics of aluminum alloys using a "deep neural network (DNN)" that was pre-trained for parameter initialization. The results showed that DNN is more accurate and more broadly applicable than "support vector regression (SVR) and shallow neural networks (SNN)", indicating its potential for a data-driven material design that can be extended to other materials. However, DNN's limitations include its reliance on small datasets.

VarolÖzkavak et al., (2023) used artificial intelligence methods "convolutional neural network, deep learning algorithm, artificial neural network and random forest regression (CNN, ANN, RFR)" to be prepared the mechanical properties (hardness, bending strength) of AA 2024 Al alloys following being aged at different temps and duration. The best results were obtained for PM and FD 2024 Al alloys with CNN "(RMSE 0.09068, R-Squared 0.93476, MAE 0.06734)" as well as "(RMSE 0.08578, R-Squared 0.94166, MAE 0.06212)", respectively limitations included reliance on available experimental data.

Arpitha et al., (2023) used a central composites design-response surface technique & artificial neural network architecture to optimize the synergistic impact of sugarcane bagasse & aluminum micro-fillers (1.38 to 5.62 wt. %) of epoxy polymer composites. Both sugarcane bagasse and alumina micro-fillers affect mechanical properties, with 3.5 wt. % optimizing flexural qualities. Epoxy resin composites have better physical, thermal and mechanical characteristics, yet microscopy shows uniform filler distribution, verifying the model's correctness.

Kordijazi et al., (2021) evaluated the wetting properties of graphite, NiAl3 and SiC-containing Al-Si alloys and Al composites with metal matrix using theoretical, experimental & machine learning (ML) approaches. ML models with significant positive correlations ($r > 0.9$) between predicted and observed water contact angles, showing robustness, include regression, ANN, "chi-square automatic interaction detection (CHAID)", XGBoost and random forest. Mechanical abrasion, etching and graphite addition all raise contact angles. With constraints due to the complexity of multiphase

alloy systems, they give interesting insights for predicting wetting qualities and comprehending physical events connected with alloy wettability.

Rajput et al., (2022) aims to enhance stir casting for marine and aerospace applications of hybrid metallic matrix composites (Al-HMMC) based on aluminum. They use a decision tree regression model to forecast Al-HMMC's mechanical properties properly. The model predicts Ultimate Tensile Strength with 92.029% accuracy. In experimental validation on Al7075 and Al6061 matrices, anticipated and real UTS values differ by less than 10%. Machine learning can minimize experimental costs and time for improving Al-HMMC characteristics, according to the research.

According to Deng et al., (2020), machine learning (ML), namely the "SMOreg/puk technique", can forecast the Cu-Al alloy's mechanical characteristics in metallic powder with an accuracy that is higher than that of five other models. "Cu-12Al6-Ni" alloy with expected "tensile force (390 MPa) & hardness (HB 139)" was produced utilizing the SMOreg/puk model, offering a rapid and efficient method for material synthesis & characterization using chemical composition and porosity as descriptors. The research provides important insights into composition design, even though model generalization can have limitations.

According to Devadiga et al., (2019), "scanning electron microscope (SEM)" blend powder morphology as well as sintered composite structure characterization are used to predict density and hardness in "multi-walled carbon nanotubes (MWCNT)" coupled with "fly ashes (FA/Al)" composites using artificial neural networks (ANN) that connect them with encouragement quantity, ball milling duration and sintering time exploratory mechanical property determination. Based on how property dispersion & augmentation are affected by reinforcing content, ball milling duration and sintering time, ANN predicts mechanical properties. The trial's scope can restrict the range of variables and their generalizability.

Wiciak-Pikuła et al., (2020) used "multilayered perceptron (MLP)" artificial neural networks to develop effective face grinding tool usage models for forecasting with "aluminum matrix composites (AMC)" that include 10% SiC. The models were evaluated using mean square error and limitations in "tool flank wear (〖VB〗_B)" as well as "tool corner wear (〖VB〗_C)" forecasting during machining were addressed.

Wang et al., (2021) used machine learning to predict the creep life of Cr-Mo steel using time-temperature parameters Larson-Miller parameter, Manson-Haferd parameter and Manson-Succop parameter (LMP, MHP, MSP) demonstrating enhanced precision with random forest algorithms while offering valuable insights into influencing features for steel creep properties. Limitations include the dependence on conventional creep research knowledge and potential generalization issues.

Liu et al., (2023) suggested a deep learning-based technique based on convolutional neural networks to forecast damage and deformation in self-piercing riveted joints of aluminum alloys and carbon fiber-reinforced composites. The model solves the problems of complicated simulation and high experimental costs in self-piercing riveted (SPR) joint analysis by reliably predicting section parameters with average accuracies of 95.80% for riveted head height, 95.68% for residual thickness and 92.40% for rivet spread.

Hajilounezhad et al., (2021) effort was to accurately classify and predict the morphology and mechanical properties of vertically oriented carbon nanotube (CNT) forests through the use of an image-based machine learning technique and a physics-based simulation called CNT Net. This will enable high-throughput material discovery. By using synthetic images to train CNT Net, the technique has shown >91% accuracy in categorizing CNT characteristics and superiority in stiffness and buckling load prediction over physical parameter-based predictors. Constraints include the intricacy of the regulating processes and the extensive range of experimental parameters.

Katırcı and Yıldız (2023) used ML algorithms Multi-layer Perceptron, Random Forest and Extreme Gradient Boosting (MLP, RF, XGBoost) with improved hyper parameters to forecast Al2O3-Cr2O3 ceramic fracture behavior. RF predicted Cr2O3 ratio as critical for relative density, diameter for fracture strength and thickness for total crack length, matching actual results. Genetic Algorithm discovered best solution (0.7% Cr2O3, 28.5 mm diameter, 2.2 mm thickness, 325.8 MPa fracture strength). Surface response experimentation and leave-one-out cross-validation were used. Results help forecast material properties, but generalization concerns and dataset features restrict them.

Thirumoorthy et al., (2019) used of stir casting to produce Al6061 MMCs with blended MgO and Si3N4, with tensile properties assessed using a novel hybrid approach combining "K-nearest neighbor (KNN)" and "ant lion optimization (ALO)" methods. Validated against a decision tree (DT) classifier, the results show that KNN-ALO was effective at predicting tensile and hardness properties of composites, contributing to advancements in material processing and characterization.

The B-AGRU model's development overcame challenges in capturing complicated patterns and connections, hence addressing the difficulty of forecasting mechanical features in Alumina Composites.

1.1 Contribution

- The study gathers dataset for testing and training.
- Pre-processing data entails Z-score normalization and robust cleaning for noise reduction, which guarantee fair along with consistent comparisons and improve dataset quality.
- Using PCA is a critical step that reduces the dimensionality of the data while preserving important information, improving algorithmic efficiency.
- The B-AGRU method is a powerful machine-learning approach used in this study to forecast the mechanical characteristics of aluminum alloys.

The remaining part of the study: part 2 discusses the methodology, part 3 assesses the efficiency of the proposed method and part 4 concludes the paper.

2. METHODOLOGY

In the section, the research forecasted the mechanical properties of aluminum alloys using the potent machine-learning technique known as the B-AGRU technique. Gathering data set, the data cleaning and z-score normalization is used for pre-processing. The feature extraction using a PCA, Figure 1 illustrates the structure of methodology.

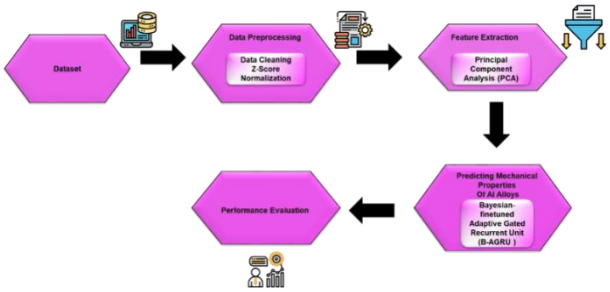

Figure 1. Overview of methodology.

2.1 Data set

In this research, a total of 130 datasets were acquired from material matching experiments (Devi et al., (2020)). These datasets encompass various compositions of aluminum alloys, yield strength, hardness and tensile strength of aluminum composites, with matching values. The specific details of these values are presented in Table 1.

Table 1. Mechanical properties of aluminum alloys.

Sl. number	Cr %	Mn %	Si %	Cu %	Fe %	Z r%	Al %	Zn %	Mg %	Other	Yield strength	Tensile strength	Hardness
1	0	0.3	0	79.1	4.7	0	11	0	0	0	850	185	-70
2	0	0	0.6	0	0.6	0.1	96.3	0	1.5	0	135	60	-44
3	0	1.2	2.2	0.2	0.7	0	95	0	0.5	0	200	170	-44
-	-	-	-	-	-	-	-	-	-	-	-	-	-
-	-	-	-	-	-	-	-	-	-	-	-	-	-
128	0	0.55	11	0.35	0.65	0	86.05	0.35	0.45	0.2	180	380	-80
129	0	0.45	1.5	0.05	0.55	0	90.5	0.1	6.5	0.2	219	250	-65
130	0.1	1	0.8	4.6	0.8	0	87.8	0.8	1.8	0.2	370	250	-100

2.2 Data pre-processing

Data pre-processing is the process of preparing and altering raw data before utilizing it in machine learning or analytical algorithms. To provide a constant scale for accurate modeling and analysis throughout the prediction phase, Z-score normalization is utilized to normalize the features. Data cleaning is used to resolve missing or incorrect values as part of the data pre-treatment procedure to forecast the mechanical characteristics of Alumina Composites.

2.2.1 Data cleaning

Data cleaning, an essential part of data preparation, is locating and fixing mistakes, inconsistencies and inaccuracies in a dataset to improve its dependability and quality. As part of this procedure, missing values are handled via imputation or elimination; errors in data inputs are identified and corrected as well as formats are standardized to promote uniformity. To verify the integrity of the data, it entails evaluating it against predetermined rules or statistical criteria. Data cleaning seeks to improve the accuracy and efficacy of data-driven decision-making processes by methodically resolving these problems and producing a cleaned dataset that provides a strong basis for further analysis and modeling.

2.2.2 Z-score normalization

In predicting the mechanical properties of Alumina Composites, Z-score normalization entails adjusting the raw data to have a mean of zero and a standard deviation of one, maintaining uniform scales for different features

and improving model performance. A data preprocessing method called Z-score normalization, commonly called standardization, was used to convert numerical data to comply with a standard distribution. It includes dividing by the standard deviation after considering the data's mean. The values of attribute B are standardized under their standard deviation and mean using the normalization approach. The following Eq. (1) converts a value of B to$\hat{b}$:

$$\hat{b} = \frac{b-\mu(b)}{\partial(b)} \quad (1)$$

Where $\partial(b)$ reflects the properties′ standard deviation $B, \&\mu(b)$ shows the average value.
The method works well in stationary environments because B's minimum and maximum values are known. It struggles with non-stationary time series since their standard deviation and mean change with time.

2.3 Feature extraction using Principal component analysis (PCA)

To extract features and forecast the mechanical properties of alumina composites, it was done using principal component analysis (PCA). By lowering the dimensionality of the data while maintaining crucial information, this method aids in enhancing our comprehension of the mechanical characteristics of the material. PCA is a statistical method that uses data to create a model. It takes a group of variables that are related to each other and transforms them into a least number of innovative parameters that are non-related to each other. These innovative parameters retain a significant amount of the actual data's information. Let W is the input data, where all column represents a sequence of m-dimensional inputs. Furthermore, it is important to note that the mean of each function in the set of values is zero $(E(W) = 0)$. A data matrix in its original form consists of m samples and n variables, which can be represented as following Eq. (2):

$$W = [w_1, w_2, \dots, w_m]^S = \begin{pmatrix} w_{11} & \cdots & w_{1n} \\ \vdots & \ddots & \vdots \\ w_{m1} & \cdots & w_{mn} \end{pmatrix} \quad (2)$$

Data on environmental parameters and performance criteria can be converted into a new occurrence space using Principal Component Analysis (PCA), which preserves as much of the original data as is practical. To do this, the directions with the most variance in the input information sets are found and they are predicted into a new subspace with the same or fewer extent than the original space.

Therefore, an orthonormal transformation Y can be employed to transfer$W$ to a novel space S in the following Eq. (3):

$$S = YW \quad (3)$$

The orthonormal vectors that constitute the S-matrix of values are obtained through a linear mixture of components from the W-matrix. This combination describes the relationship between the samples. The Smatrix of covariance is defined as Eq. (4):

$$D_S = YD_wY^S \quad (4)$$

The variable D_w represents the matrix of covariance for the variable$W$.

The weighting matrices Y can be obtained by solving the eigenvalue Eq. (5):

$$(D_s - \lambda J)f_j = 0 \quad (5)$$

The covariance matrix contains the bilateral co-variances between the several input variables. Subsequently, the eigenvectors and eigenvalues for the matrix of covariance are decomposed (as shown in Eq. (5). The resulting eigenvectors represent the new orthogonal elements, referred to as "principal components, with their magnitude determined by the related Eigen values". After arranging the eigenvalues and the related eigenvectors in a decreasing order, the PC will follow the same order. The first principal component will possess the highest variance, indicating the most significant information. The subsequent principal component will exhibit the second highest variance and so on. It is important to mention that the main components obtained are not associated with one another, regardless of the correlation between the input parameters.

2.4 Predicting mechanical properties of AL alloy using for Bayesian- fine-tuned Adaptive Gated Recurrent Unit (B-AGRU)

The Gated Recurrent Unit (GRU) neural network and Bayesian Optimization (BO) are used in the B-AGRU technique to forecast the mechanical characteristics of aluminium alloys. BO is used to tune hyper parameters. Algorithm 1 illustrate the B-AGRU

2.4.1 Bayesian Optimization (BO)

The Bayesian Optimization (BO) technique, utilized as a model-based hyper parameter-tuning strategy, leverages surrogate function for simulating the conditional probability of validation set performance with provided hyper parameters. Unlike grid / random searches, BO records earlier assessments, minimizing unnecessary calculations for unfavorable hyper parameters. The acquisition function chooses promising hyper parameters for the next iteration, enhancing tuning effectiveness in a shorter assessment time. The proposed model incorporates BO algorithm techniques into the dynamic ensemble module to achieve optimum hyper parameter tuning. The BO approach is made up of five primary components: hyper parameter distance, OF (forecasting error based enhanced validation data), acquisitions function, history of

assessments and surrogate function. The approach leverages "tree-based Parzen window estimation (TPE)" for the probabilistic estimation of the surrogate function and the anticipated improvement acts as the acquisition function A, as shown in Eq. (6).

$$a_{g^*}(V) = \int_{-\infty}^{g^*} (g^* - g) Q(g|v) dg, \quad (6)$$

Where$g$ is the $\varrho\mathcal{F}$ and g is the $\varrho\mathcal{F}$ threshold, assuming the hyper parameter selection$v$.

2.4.2 Fine tuned Gated Recurrent Unit (GRU)

The GRU is a "recurrent neural network (RNN)" that is an expanded version of "long short-term memory (LSTM)" unit. The GRU is a simplified model with two gate functions: the update gate, which determines how much previous information is preserved and the reset gate, which commands the integration of past information with the current input. This is in contrast to the LSTM's Input gate, forgetting gate, & output gate are the three gate functions.

The formula for calculation at time t is as following Eq. (7-10).

$$r_t = \sigma_{sig}\,(W_r x_t + U_r h_{t-1}) \quad (7)$$

$$z_t = \sigma_{sig}\,(W_z x_t + U_z h_{t-1}) \quad (8)$$

$$\tilde{h} = \emptyset_{tanh}(z_t = \sigma_{sig}\,(W_h x_t + r_t \circ U_h h_{t-1}) \quad (9)$$

$$h_t = (1 - z_t) \circ h_{t-1} + z_t \circ \tilde{h}_t \quad (10)$$

The current hidden node's candidate value is represented by $\tilde{h}_t$in the formula above, while the activating value of the hidden node's output is represented byh_t. The reset gate is represented byr_t, while the update gate is byz_t. °Denotes the multiplier element-wise. The activation functions $\sigma_{sig}\varphi_{tanh}$are responsible for activating control gates and candidate states, respectively. The $sigmoid$ and $tanh$ functions' expressions are Eq. (11-12):

$$sig(x) = (1 + e^x)^{-1} \quad (11)$$

$$\tanh(x) = 2^* sig(x) - 1 \quad (12)$$

This study employs an enhanced GRU model to enhance the precision of wind power predictions, aiming to achieve superior prediction accuracy. Algorithm 1 illustrates the GRU.

The input parameters are represented by X and the analyses of alumina alloys mechanical properties were determined by Y. The following represents a representation of the hybrid Eq. (13):

$$y = f_{hybrid}(x) \quad (13)$$

Where, a function called f_{hybrid} combines the Gated Recurrent Unit (GRU) and the outputs of Bayesian Optimization (BO). The goal is to increase forecast accuracy by utilizing the advantages of both methods. The GRU model's features or hyper parameters might be optimized using the BO as one potential strategy. Whereas the GRU detects sequential relationships in the data, the BO model learns the mapping from input parameters to desired attributes.

The hybrid Eq. (14) is shown in the following simplified form:

$$y = GRU(X; \theta_{GRU}) + BO(X; \theta_{BO}) \quad (14)$$

- The GRU model's output, represented as$GRU(X; \theta_{GRU})$, has parametersθ_{GRU}.
- TheBO model's output, represented as$BO(X; \theta_{BO})$, has parametersθ_{BO}.

It is possible to tune theθ_{GRU} and θ_{BO}model parameters during training. With the assistance of the Bayesian technique, this hybrid strategy aims to represent both the sequential dependencies in the data and the optimization of the parameters. The specifics of our data and the objectives of the prediction model will determine how the implementation is performed out.

Algorithm 1: B-AGRU

```
Import necessary libraries
from agru model import create agrumodel  # Assume you have a function to create AGRU model
from Bayesian optimization import optimize with BO
Assume you have a function for Bayesian Optimization
Sample data (replace with your actual data)
X train, y train = generate training data()
Step 1: Bayesian Optimization to optimize AGRU hyperparameters
Best params = optimize with bo(X train, y train)
Step 2: Train AGRU model with optimized hyperparameters
Agru model = create agrumodel(best params)
agru model. Fit(X train, y train)
Step 3: Make predictions using the trained AGRU model
Agru predictions = agru model. Predict(X test)
Step 4: Use Bayesian Optimization to further refine predictions
Refined params = optimize with bo(X test, agru predictions)
Step 5: Train final AGRU model with refined hyperparameters
Final agru model = create agrumodel(refined params)
final agru model. Fit(X train, y train)
Step 6: Make final predictions
Final predictions = final agru model. Predict(X test)
Evaluate the final predictions
evaluate(final predictions, true values)
```

3. PERFORMANCE EVALUATION AND DISCUSSION

The mechanical properties of Alumina composites are predicted by implementing a B-AGRU in Python. Key material attributes are included in the dataset. Tensor Flow or PyTorch are used in the Python code to build GRU. An adequate Graphics Processing Unit (GPU) and a minimum of 8GB RAM is needed for the experiment to educate the computer effectively. We analyze the proposed method metrics of performance: RMSE "(Root Mean Squared Error)", MAE "(Mean Absolute Error)" and R Squared. Comparisons of our proposed method are deep neural network (DNN) (Yu et al., 2021), support vector regression (SVR) (Yu et al., 2021) and shallow neural network (SNN) (Yu et al., 2021).

Figure 2 shows a comparison of the B-AGRU algorithms predicted and real tensile strength values. The figure shows that the B-AGRU algorithm was able to produce a better fit between the points and the regression line. Just one of the 13 data points, which differ dramatically from the regression line, stands out as an outlier. The general data point alignment with the regression line highlights how well the algorithm predicts the tensile strength of aluminum alloys.

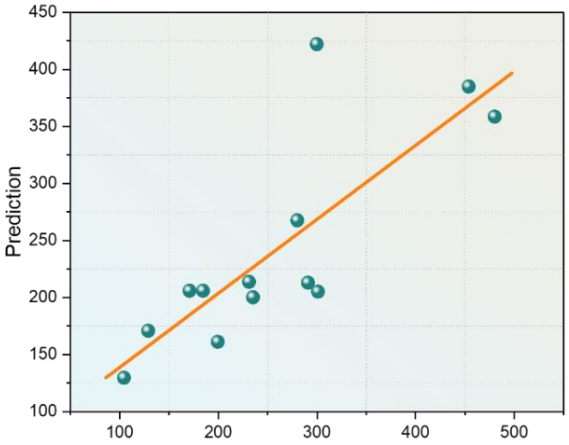

Figure 2. B-AGRU-based Actual vs. Predicted tensile strength.

An analysis of yield strength predictions provided by the B-AGRU algorithm is shown in Figure 3 about actual values. Closer examination of the plot reveals that the residuals generated by the B-AGRU method better fit the data. To be more precise, the figure demonstrates that the B-AGRU method fits the regression line better when evaluating the yield strength, which suggests a higher correlation between the expected and actual values.

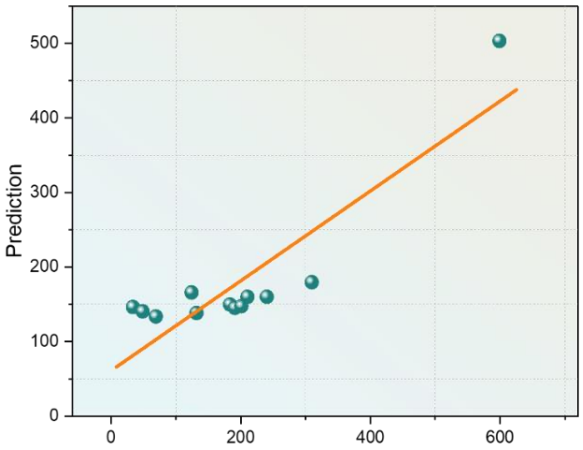

Figure 3. B-AGRU-based Actual vs. Predicted Yield Strength.

The "actual and predicted" hardness values for B-AGRU are shown in Figure 4. Notably, five or so data points depart from the predicted fitting zone. Of them, three or out of the total of 13 points do not match the regression line, making them stand out. The outliers display a notable divergence from the regression line, indicating a noteworthy departure from the overall pattern seen in the other data points.

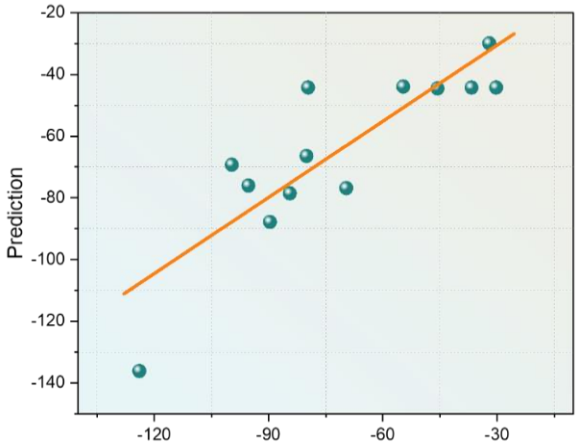

Figure 4. B-GRU-based Actual vs. Predicted Hardness value.

A statistic known as the RMSEestimates the mean variance between the results that were expected and those that weren't. the mean difference between results as predicted and as observed. The value of square root of the average for the squared differences between expected and actual values is calculated. A lower RMSE suggests that the method B-AGRU predictions are more accurate. Figure 5 and Table 2 illustrate the RMSE values. Compared to existing DNN-22, SNN-25 and SVR-28, our proposed method B-AGRU-20 was lower. Compared to existing approaches, the B-AGRU improved the predicting alumina composites' mechanical characteristics.

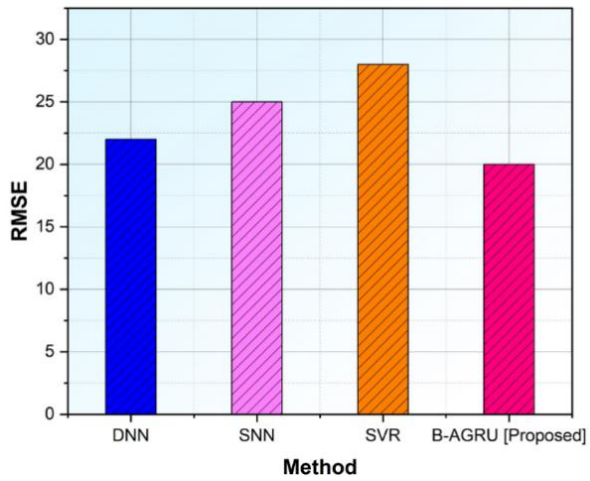

Figure 5. Outcome of RMSE.

Table 2. Values of RMSE.

Method	RMSE
DNN	22
SNN	25
SVR	28
B-AGRU [Proposed]	20

MAE is yet another statistic used to assess the prediction model's accuracy. The percentage differences between the expected and actual values are averaged. Like RMSE, MAE evaluates the extent to which the B-AGRU predictions correspond to the actual values. It is frequently used in conjunction with other assessment metrics to evaluate the B-AGRU overall performance. Figure 6 and Table 3 depict the response time values. Our suggested approach was lesser than the existing method such as DNN-13, SNN-15 and SVR 14. The B-AGRU-10 enhanced in predicting alumina composites' mechanical characteristics when compared to existing methods.

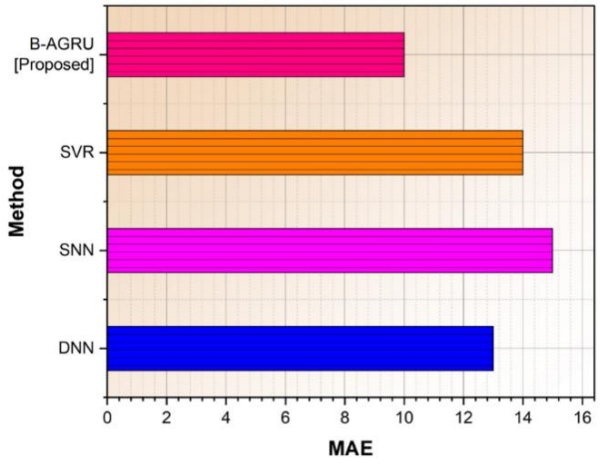

Figure 6. Outcome of MAE.

Table 3. Values of MAE.

Method	MAE
DNN	13
SNN	15
SVR	14
B-AGRU [Proposed]	10

R-squared reflects the fraction of the variation in the dependent variable that is predicted by the independent variables. A higher R-squared value indicates a more accurate match. R-squared is computed as the explained variance divided by the total variance. Our proposed method is higher B-AGRU- 97 than the existing methods DNN-96, SNN-94 and SVR-93 as shown in Figure 7 and Table 4. It shows that our proposed method B-AGRU successfully predicts alumina composites' mechanical characteristics.

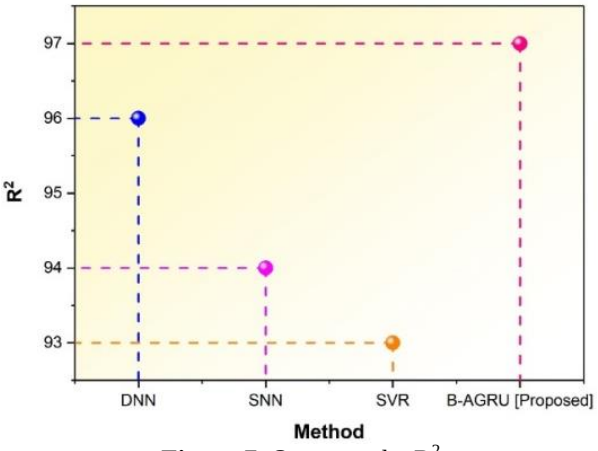

Figure 7. Outcome the R^2.

Table 4. Values of R^2.

Method	R^2
DNN	96
SNN	94
SVR	93
B-AGRU [Proposed]	97

4. CONCLUSION

The article offers a novel strategy for overcoming the difficult task of acquiring the properties of aluminium alloys required for component production. The study presents a very successful prediction model for mechanical properties including tensile strength, hardness and yield strength by using machine learning, most especially B-AGRU. The B-AGRU technique performs better at predictions because it uses data for training and testing, along with a careful preparation procedure that includes cleaning and Z-score normalization. The effectiveness of the technique is further improved by including Principal Component Analysis (PCA) for feature extraction. Metrics such as

RMSE-20%, MAE-10% and R-squared-97% show that performs better than conventional approaches. This represents not only a major breakthrough in materials science but also advances the more general objectives of sustainability and efficiency in alloy development and production processes. With different reinforcing materials and production methods, alumina composites might be intricate. Because these composites are so different, it becomes difficult to predict their mechanical properties. Higher-level insights into the behavior of the material can be obtained by using sophisticated characterization methods, such as imaging and in-situ testing. Predictive model improvement and refinement are possible with this data.

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