Experimental Study and Neural Network Model to Predict Formability of Magnesium Alloy AZ31B

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Abstract: Magnesium alloy is an emerging smart metal used in various industries like automotive and aerospace industry, due to their lightweight and excellent strength-to-weight ratio. Formability, a critical factor in manufacturing processes, determines the alloy's ability to undergo deformation without fracture or defects. Fuel economy and environmental conservatives are the key desirable factors in selection of magnesium alloy sheets. Magnesium alloy sheets have low formability at room temperature due to their hexagonal closed-packed microstructures. As the magnesium's formability at room temperature is considerably low, stretch forming tests are conducted at moderate temperatures. For this purpose, commercially available AZ31B magnesium alloy sheet of 1.1mm thickness has been used and tested at room temperature, 25 degree to within medium temperatures range and at a higher strain rate of 0.01/s. The main objective of an experimental study to predict the formability of magnesium alloy sheets is to gather data through controlled tests and measurements. This data and Forming Limit Diagram (FLD) can be used to analyse the formability of material, it defines failure criteria. On the other hand, using a neural network to predict formability involves training the network on the collected experimental data. Once trained, the neural network can predict the formability of new magnesium alloy sheets based on their characteristics, offering a faster and potentially more accurate prediction method compared to traditional models. This work explores into the realm of regression modelling utilizing neural networks, a powerful subset of machine learning techniques. It begins with a discussion on the setup of machine learning models, emphasizing the crucial steps involved in data preprocessing, model selection, and evaluation.

Keywords: AZ31B magnesium alloy sheet, formability, stretch forming, forming limit diagram, neural network, regression modelling.

1 Introduction for Stretch Forming

In recent years, magnesium alloys have attracted a lot of attention because of their lightweight properties and among the diverse range of metallic alloys, magnesium alloys have emerged

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as attractive candidates for lightweight structural applications across industries such as automotive, aerospace, and electronics.[1] Magnesium alloys have remarkable ratios of strength to weight, corrosion resistance, and thermal conductivity, making them well-suited for applications where weight reduction and durability are paramount.[2] Hot working, performed at elevated temperatures, has the potential to enhance the material's ductility during forming processes. The primary deformation mechanisms involved include the activation of twinning and the basal slip mechanism. When temperatures reach 200°C and beyond, certain basal planes have the propensity to become activated.

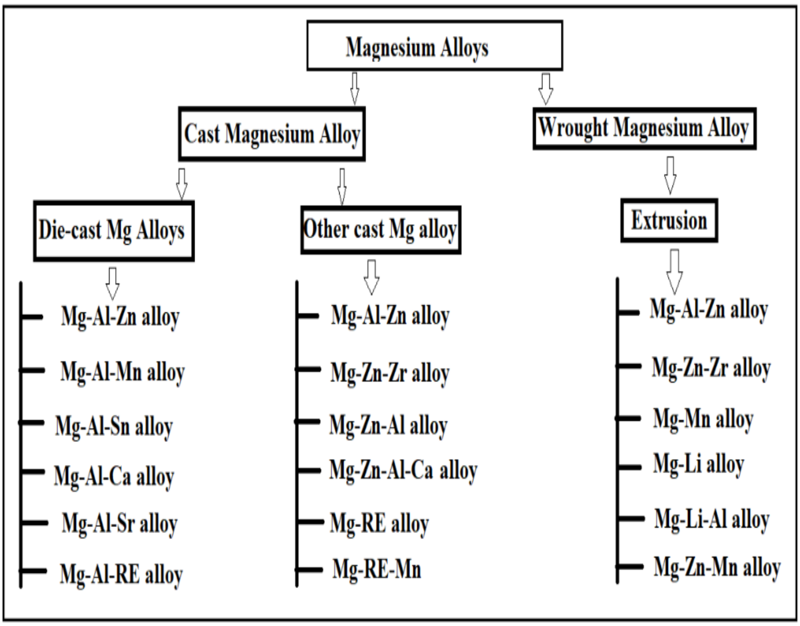

Fig. 1. Flow chart indicating different types of magnesium-based alloys.

Different types of magnesium-based alloys are shown in Fig.1. Among these alloys, AZ31B stands out for its excellent combination of mechanical properties and formability, making it a popular choice for sheet metal fabrication. AZ31B – magnesium alloy is a wrought magnesium alloy which offers good strength in room temperature.[3] It is a widely available alloy compared to other magnesium grades. However, ensuring the quality and performance of AZ31B sheet metal remains a critical challenge for manufacturers and researchers alike. As industries continue to seek lightweight alternatives for structural components, understanding the formability of AZ31B becomes paramount for efficient manufacturing and design optimization.[4] Plastic deformation, a fundamental concept in materials science and engineering, underpins the formability of metallic alloys and plays a crucial role in shaping their mechanical properties. When subjected to external forces beyond their elastic limits, materials undergo plastic deformation, resulting in permanent changes in shape and structure.[5] Understanding the mechanisms governing plastic deformation is essential for optimizing manufacturing processes and ensuring the reliability and performance of engineered components. As earlier said magnesium Alloy AZ31B is a wrought alloy primarily composed of magnesium, aluminum, and zinc, with nominal compositions of approximately 3% aluminum and 1% zinc.

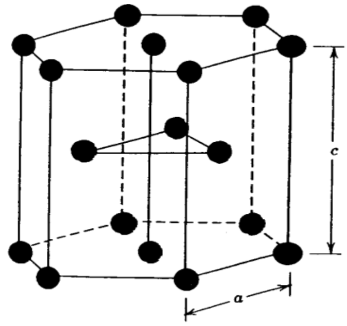

Fig. 2. Hexagonal Close Packed Crystalline Structure of AZ31B Mg alloy, a- Edge length of HCP, c- Height of HCP

The various lightweight alloys like titanium, this alloy has a hexagonal close-packed crystalline lattice structure as shown in Fig.2. with a 74% packing factor,[6] which affects its formability and mechanical capabilities. Grain boundaries & dislocations, which define AZ31B's distinct microstructure, are important factors in defining how the material responds to outside forces and deformation processes. Plastic deformation in magnesium alloys, including AZ31B, happens mostly because of dislocations moving within the crystal lattice. Dislocations, which represent defects or irregularities in the atomic arrangement, facilitate the reorganization of atoms under applied stress, enabling the material to undergo shape changes without fracturing. The presence of edge dislocations and screw dislocations within the lattice structure allows for the accommodation of external forces and the redistribution of stresses during deformation.

Formability is the property of a material that allows for plastic deformation without breaking and it is a critical parameter in the manufacturing of components from magnesium alloys like AZ31B. Achieving optimal formability requires a deep understanding of the alloy's microstructural features, mechanical behavior, and the complex interplay between processing parameters and material properties. A few variables, such as grain size, texture, temperature, strain rate, and processing methods, affect how formable AZ31B is. The alloy's microstructure evolves during manufacturing processes such as casting, rolling, and heat treatment, leading to changes in mechanical properties and formability characteristics. Understanding the relationship between microstructure and formability is essential for predicting material behavior under different forming conditions and optimizing manufacturing processes for enhanced product quality and performance.[7] Experimental studies serve as a cornerstone in investigating the formability of mg alloy AZ31B.

1.1 Experimental Work

1.1.1 Experimental Setup for Stretch Forming

Stretch forming is essential to the production of magnesium alloy the AZ31B sheet metal parts because it allows for the construction of complex shapes while maintaining dimensional accuracy and material integrity. This section presents the experimental approach used to explore the stretch forming behavior of AZ31B sheet metal and evaluate its effects on quality parameters. A biaxial stretch forming test was conducted on a 1.1mm thick sheet of magnesium alloy AZ31B. [8] Rectangular specimens were prepared as per the ISO 12004 standard and kept at a constant height of 150mm, with varying widths of 150mm, 125mm, 100mm, 75mm, and 50mm. [9]

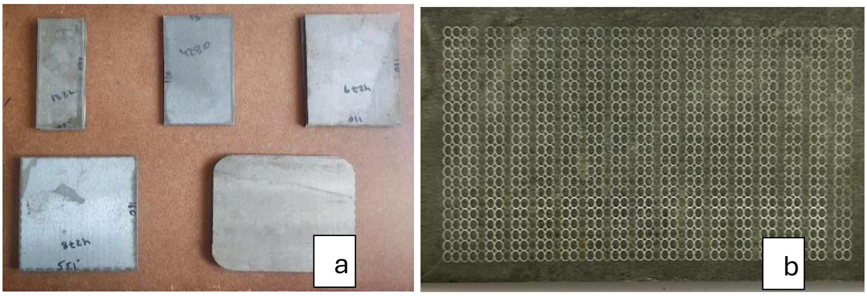

Fig. 3. (a) Specimens before etching and (b) One sample after etching

Because the CNC wire cut EDM method can retain formability by avoiding high cutting forces associated from shearing,[10] It was chosen for sample cutting over narrower widths like 25mm.[11] After cutting, a laser engraving equipment etching a circular pattern is used to evaluate deformation on the samples as shown in Fig.3.[12] MOLYKOTE 1000 lubricant is applied to minimize friction.[13] Multiple Nakazima tests were performed using a 50mm diameter hemispherical punch, with hot forming equipment utilized as depicted in the Fig.4.[14]

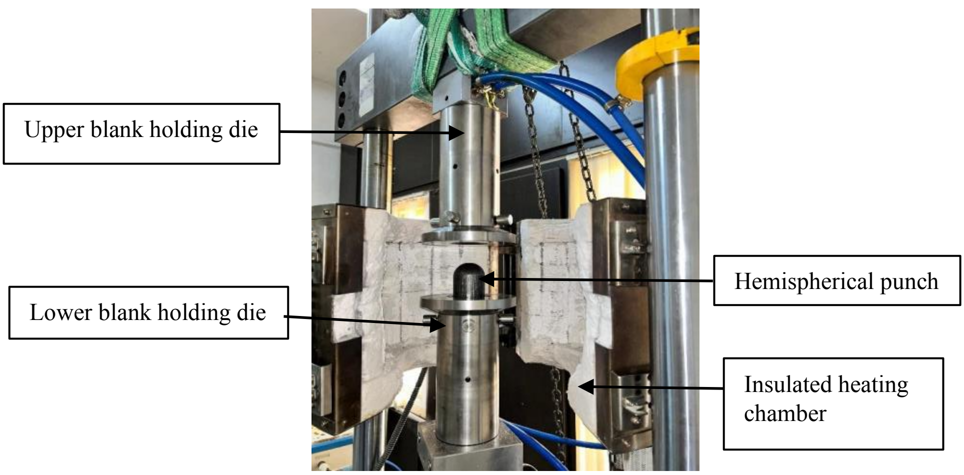

Fig. 4. Hot-forming apparatus for major diameter stretching operations

1.1.2. Methodology for stretch forming

In experimentation, stretch forming tests were conducted on specimens at Room temperature (25°C), 125°C, and 175°C, employing a strain rate of 0.01mm/s that resulted in perfect cracks in all cases.[15] To conduct stretch forming at elevated temperatures, specimens preheated to the desired temperature need a soak period of 20 to 30 minutes for thermal equilibrium within the heating chamber. To minimize heat losses, ceramic wool was employed as an insulating material.[16] A 300-bar hydraulic pump was used to apply an initial empty clamp pressure of 180 bar,[17] which caused a bead to form on the flat sheet prior to the stretch forming process employing higher and lower dies.[18] Throughout the experiment, the load-displacement curve was monitored on a computer screen via a data acquisition system. The key challenge lies in accurately predicting the moment when the specimen starts to fracture, marking the onset of the crack.[19] Once the crack point is reached, the experiment is halted. The equipment is linked to a data acquisition system for real-time data interpretation. After gathering the data, graphs were obtained showing load versus time and load versus displacement from Fig.5. Before proceeding with the next experiment and removing the previous specimen from the setup, the specimen must be given some time to come back to room temperature.

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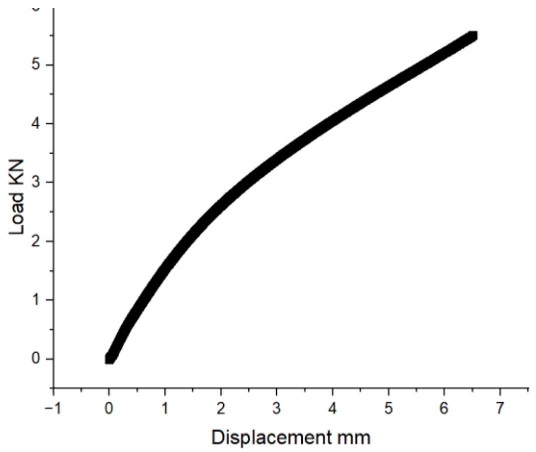

Fig. 5. Load vs Displacement graph plotted at room temperature

Following stretching, the circular shapes may transform into ellipses as shown in Fig.6. These ellipses major and minor diameters are noted in order to create the Forming Limit Diagram (FLD).

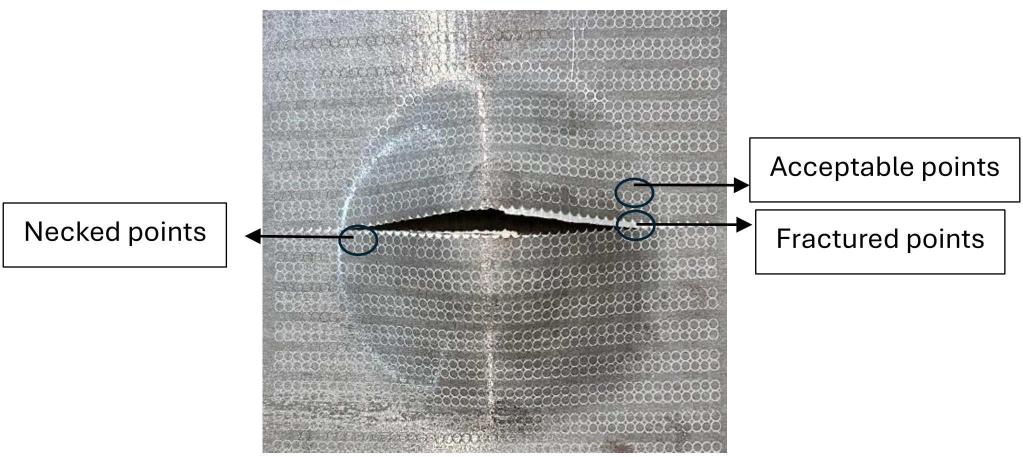

Fig. 6. Formation of fractured, necked and acceptable points

2 Forming Limit Diagram (FLD) Construction

Understanding how materials behave under stress is crucial for a wide range of industrial applications. While knowing the Ultimate Tensile Strength is helpful, it's not sufficient for predicting failure in sheet metal forming. Engineers rely on the Forming Limit Diagram (FLD), a comprehensive tool that graphically illustrates the strains causing neck failure based on the strain path.[20] The FLD considers numerous factors such as metal quality, sheet thickness, surface conditions, and forming methods like punch type, test speed, and temperature.[21]

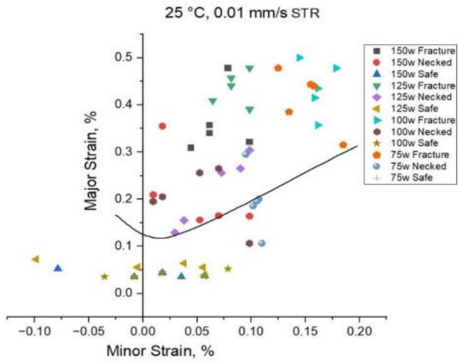

Fig. 7. Experimental FLD displaying the Forming Limit Curve at a strain rate of 0.01 mm/s and at a temperature of 25°C

Fig.7. shows the experimental FLD having a major strain, % of at a strain rate 0.01mm/s and at a temperature of 25°C. Similarly, Fig.8. shows the FLD having a major strain, % of 0.28 at 125°C and 0.32 at 175°C. Notably, the FLD is adaptable to parts of any shape. Creating the FLD involves subjecting metal samples to controlled strain using a 50 mm diameter punch until fracture.[22] A circular pattern is often applied to monitor strain distribution during experimentation, and multiple Nakajima tests were conducted on each sample to establish an average plot point.[23]

Observations from FLD experiments reveal distinct stress states like uniaxial, biaxial, and plane-strain conditions, which are vital for understanding material behavior.[24] Engineers plot multiple ellipses around the necking zone to visualize forming limits accurately. Major and minor diameters can be measured using a stereo-zoom optical microscope for microscopic analysis, which facilitates the computation of actual strains.[25] Experiments with fluctuating strain rates and temperatures provide important information about the behaviour of materials under various circumstances.[26] To summarize, engineers utilize the Forming Limit Diagram as a crucial tool to forecast failures of materials in sheet metal forming operations. Its comprehensive analysis of various parameters ensures the reliability and integrity of manufactured components.

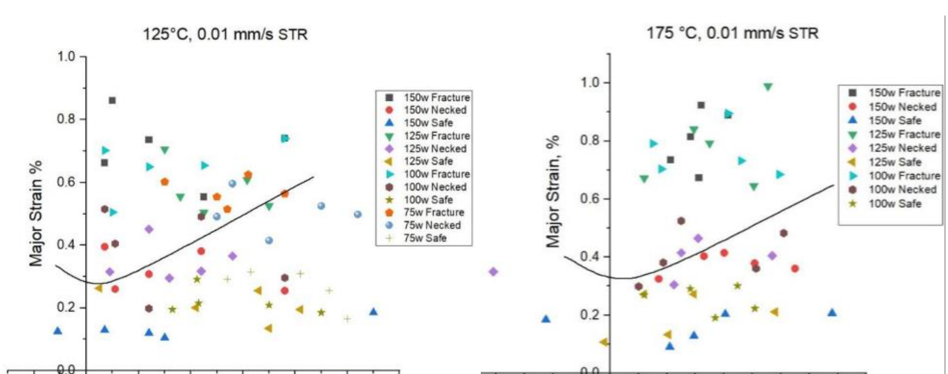

Fig. 8. Experimental FLD displaying the Forming Limit Curve at a strain rate of 0.01 mm/s and at a temperature of 125°C and 175°C

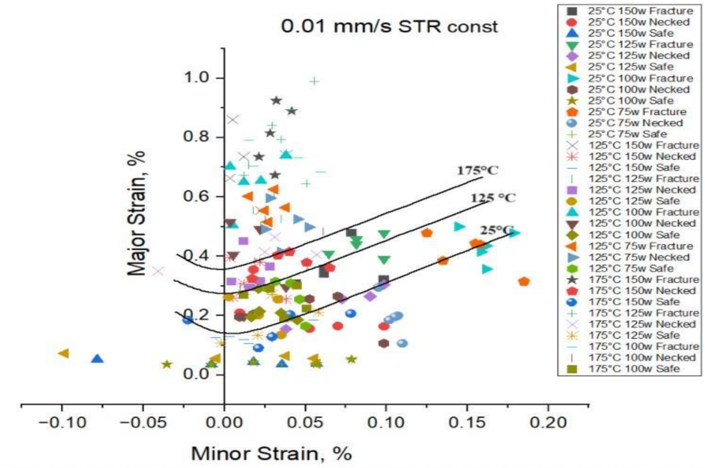

Fig. 9. Experimental FLD displaying the Forming Limit Curve at a strain rate of 0.01 mm/s and at a temperature of 25°C, 125°C,175°C

3 Regression Modelling utilizing Neural Network

3.1 Introduction

In recent years, machine learning has emerged as a powerful tool across various domains such as computer vision, natural language processing, weather forecasting, image recognition and now, even material science. Artificial intelligence and machine learning models have become increasingly popular in research, especially for understanding and forecasting the properties of metallic substances. The efficiency of machine learning mechanisms heavily relies on the datasets used to train the models. In the context of material science, the input features necessary to calculate or measure specific properties of an alloy are considered, while the output variable represents the targeted property of interest. Through extensive training, machine learning models establish quantitative relationships between these input features and the target property. Several notable studies have demonstrated the potential of machine learning in predicting metallic materials properties. Researchers have made significant contributions in areas such as accelerated search for materials with targeted properties, and defect identification in stainless steel. One noteworthy study by Amar M Chheda focused on developing a machine learning model to predict the forming limit diagrams of aluminum alloys.[27] The researchers meticulously curated a dataset, incorporating multi-dimensional data and employing rigorous data reduction mechanisms. The study by Balaji Viswanadhapalli and Krishna Chythanya Nagaraju focused on developing a machine learning model to predict the formability of magnesium alloys.[28] Ultimately, a machine learning model was trained using seven carefully selected features, including parameters from stretch forming tests. The model's accuracy was evaluated using metrics such as Root Mean Square Error (RMSE), achieving an impressive accuracy of around 94%. Similarly, Leyun Wang's work involved the prediction of tensile properties of AZ31 magnesium alloy using artificial neural networks (ANN) and support vector machine (SVM) algorithms. While the models accurately predicted tensile strength, yield strength, and ultimate tensile strength, they encountered challenges in predicting elongation accurately. However, despite the advancements in predicting various properties of metallic materials, there remains a gap in the literature concerning the prediction of the formability of magnesium alloys using machine learning models. Hence, this article aims to address this gap by exploring the prediction of magnesium alloy formability using the neural network architectures, keras dense models, ReLU, MAE, and MSE etc. This study builds upon the foundation laid by previous research in the field, leveraging machine learning techniques to contribute to the understanding and prediction of material formability, particularly in the context of magnesium alloys.

3.2 Machine Learning Model Setup

Regression analysis is a fundamental statistical method for understanding the relationship between independent and dependent variables.[29] With the advent of deep learning, neural networks have emerged as a powerful tool for regression tasks, offering flexibility and scalability. This model setup aims to elucidate the process of building regression models using neural networks, from model setup to implementation.

3.2.1 Data Preprocessing

Handling Missing Values**:** Techniques include imputation (filling missing values with a calculated estimate), deletion (removing rows or columns with missing values).
Data Splitting**:** Typically, the dataset is divided into training, validation, and testing sets, with the training set used for model training, the validation set for hyperparameter tuning, and the testing set for final evaluation.
The dataset comprises 27,911 entries across 7 columns. It includes various experimental properties such as Temperature, Strain Rate, Time in Seconds, Load in Kilonewtons, Length, and Width, with Displacement in millimeters as the target variable. The dataset covers three temperature conditions: room temperature, 125 degrees Celsius, and 175 degrees Celsius, along with a constant strain rate of 0.01 mm/s. Notably, there are no missing values in the dataset, as evidenced by an equal count of 27,911 values in each column as shown in Fig.10.

	Temperature	Strain Rate	Sp-Height	Sp-width	Time	Rel. Load	Displacement
count	27911.000000	27911.00	27911.0	27911.000000	27911.000000	27911.000000	2.791100e+04
mean	96.720827	0.01	150.0	103.465480	233.601819	1.856031	8.411602e+01
std	61.512860	0.00	0.0	34.079715	130.620462	1.528184	8.284623e+03
min	25.000000	0.01	150.0	50.000000	0.200000	0.000000	-7.050922e+01
25%	25.000000	0.01	150.0	75.000000	123.199265	0.458304	1.724557e+00
50%	125.000000	0.01	150.0	100.000000	230.597626	1.541103	3.556730e+00
75%	150.000000	0.01	150.0	125.000000	337.902222	3.056065	5.276105e+00
max	175.000000	0.01	150.0	150.000000	579.616943	6.515416	1.027256e+06

Fig. 10. Describing the dataset

3.2.2 Model Selection

Considerations include the complexity of the problem, size and quality of the dataset, computational resources, interpretability of the model, and desired prediction accuracy. Common algorithms for regression tasks besides neural networks include linear regression, decision trees, support vector machines, and ensemble methods like random forests and gradient boosting.

3.2.3 Model Evaluation

Metrics for evaluating regression models include Mean Absolute Error (MAE): Average of the absolute differences between predicted and actual values. Split the data into input features (X) and target variable (y) or split the dataset into train and validation sets, typically using a 70-30 split, which means 70% for training dataset and 30% for validation dataset. This allows you to evaluate the model's performance on unseen data.

Define the architecture of your neural network using the Sequential model of 6-600-600-1100-1 in Keras. And add layers to the model using ‘Dense’ for fully connected layers. Choose appropriate activation functions for each layer as we choose ‘relu’. Then compile the model specifying the loss function ("MSE"), optimizer ("Adam"), and metrics ("MAE"). Once compilation is done, train the model on the training data using the ‘fit ()’ function. Specify the number of epochs (iterations over the entire dataset) and batch size. Monitor the training process for convergence and adjust hyperparameters if necessary. Evaluate the trained model on the testing data to assess its performance. Calculate metrics such as Mean Absolute Error (MAE) to measure the model's accuracy as shown in Fig.12.

```
y_pred = model.predict(x_val)

from sklearn.metrics import r2_score, mean_squared_error
import numpy as np

score = r2_score(y_val, y_pred)
print(score)
print('mean_squared_error is==> ', mean_squared_error(y_val, y_pred))
print('root_mean_squared error is==> ', np.sqrt(mean_squared_error(y_val
y_pred)))
262/262 [==============================] - 1s 5ms/step
0.8863406581471613
mean_squared_error is==>  1.336022788346402
root_mean_squared error is==>  1.1558645198925357
```

Fig. 12. RMSE value and MSE value of linear regression

The linear regression model achieved an accuracy of approximately 88% by predicting displacement and an RMSE (Root Mean Squared Error) of 1.15, MSE of 1.33 in predicting the formability of Magnesium Alloy in our experimentation. These results suggest that linear regression outperformed, demonstrating superior predictive performance for this task as shown in Fig.14.

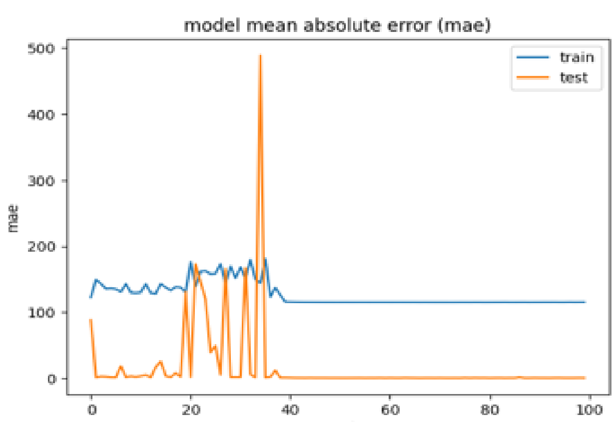

Fig. 13. Model graph of MAE for training and testing

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Actual value:

11937	125	0.01	150	100	142.798965	0.450196	2.58725
11938	125	0.01	150	100	142.998962	0.45072	2.582718
11939	125	0.01	150	100	143.198959	0.45365	2.584885

Predicted value:

```
#Predecting by passing input features
Y_pred = model.predict([[125,0.01,150,100,142.998962,0.45072]])
print('Displacement of 150H-100W at [125deg, 0.01STR,0.450729KN] is: ',Y_pred)
```

```
1/1 [==============================] - 0s 47ms/step
Displacement of 150H-100W at [125deg, 0.01STR,0.450729KN] is:  [[2.5825107]]
```

Fig. 14. Prediction of displacement by passing input features to the model

4 Results and Discussion

Using hemi-spherical punch, stretch forming experiments were conducted on 1.1mm thick sheets of AZ31B magnesium alloy to ascertain the material's formability at elevated temperatures. Each specimen undergoes numerous Nakazima tests for uniformity in this regard. The construction of FLDs is the formability metric.

To forecast the material's formability, a neural network model is developed using the data from the experiment set. Below is a summary of the findings and observations from the machine learning model and the experimental study.

4.1 Experimental Result

Under test conditions of 125°C and 175°C at 0.01mm/s strain rate, the dome reaches its maximum height. It has been observed that a blank holding pressure of 180 bar works well for applying proper bead on the specimen. Also, minimizes the possibility of crack formation around the bead prior to the forming process. Optimal forming conditions have been determined with a punch speed of 0.01mm/s and at 125°C and 175°C temperatures proving to be highly effective. The forming limit curve emphasizes how important strain rates and sample temperature are in determining formability. A closer look using scanning electron microscopy images reveals ductile fracture, which promotes good formability outcomes.

4.2 Machine learning model results

When predicting material formability, the linear regression (LR) algorithm using neural network achieved an accuracy rate close to 88%, with a root mean squared error (RMSE) of 1.15 and mean squared error of 1.33. Linear regression exhibited superior performance in predicting material formability.

5 Conclusion

To evaluate the formability of AZ31B magnesium alloy, stretch forming tests were conducted at high temperatures. Machine learning models were trained with the help of the experimental test findings. The data, including forming limit diagrams (FLD) and experimental results, indicate a notable enhancement in the material's formability at higher temperatures, thereby rendering it suitable for applications involving elevated temperatures.

Good-accuracy machine learning algorithm, LR, have been built to predict a material's formability. This algorithm can greatly minimize the requirement for extensive physical experiments. This may result in a more ecologically responsible strategy, especially if the automobile and aerospace industries use lightweight magnesium alloys.

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