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# AI-Based Prediction of Stress Concentration Factor using Neural Networks

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**ABSTRACT:** Stress Concentration Factor (SCF) is a critical design parameter in mechanical engineering, representing localized stress amplification caused by geometric discontinuities such as notches, holes, and grooves. Accurate estimation of SCF is essential for preventing material failure and ensuring structural reliability. Traditional methods for SCF determination, such as analytical equations or Finite Element Analysis (FEA), while effective, are limited in scope and computationally expensive, especially when evaluating multiple design iterations or performing real-time optimizations. This study proposes a data-driven approach utilizing The model architecture employs a Bidirectional LSTM network, capable of learning complex, nonlinear relationships within the input parameters. Experimental results demonstrate that the proposed model achieves high predictive accuracy, with a Mean Absolute Error (MAE) of 0.0007 and a model accuracy exceeding 94%. The Predicted vs Actual SCF comparison confirms the model's ability to generalize well to unseen data. Additionally, the model shows consistent training and validation behavior, suggesting robust convergence without overfitting.

## I. INTRODUCTION

Stress concentration is a common and critical phenomenon encountered in structural components, particularly at geometric discontinuities such as holes, grooves, or notches. These regions often experience elevated localized stress compared to the average or nominal stress in the rest of the structure. The quantification of this effect is represented by the Stress Concentration Factor (SCF), which is defined as the ratio of maximum localized stress to the nominal stress [1, 2]. With the rise of Artificial Intelligence (AI) in engineering, particularly in the form of machine learning (ML) and deep learning, there exists a promising opportunity to revolutionize how SCF is estimated. By training an Artificial Neural Network (ANN) on simulated data, the system can learn to approximate SCF values with high precision, bypassing the need for expensive simulations in routine use cases. This paper proposes such a method using a Bidirectional Long Short-Term Memory (Bi-LSTM) network trained on geometrical and load-related parameters. This work contributes to the body of knowledge by presenting a data-driven, real-time, and scalable method for SCF estimation, opening the path toward AI-augmented design tools that bridge computational mechanics and intelligent automation[3].

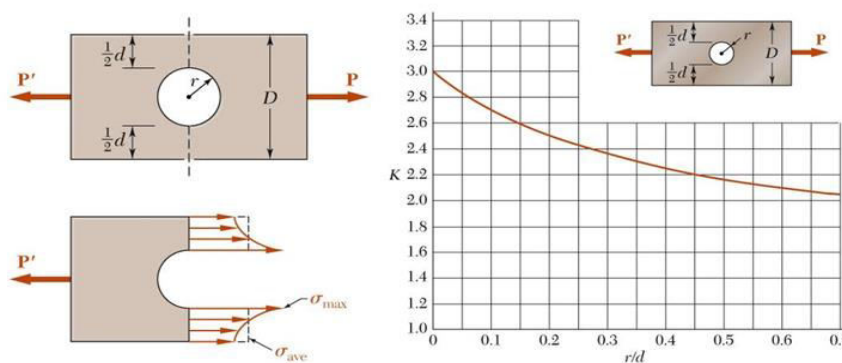


Figure 1: Stress concentration factor



## II. PROBLEM DEFINITION AND MOTIVATION

The design of critical mechanical parts such as shafts, plates, and brackets often includes complex shapes that introduce localized stress concentrations. Engineers typically perform FEA for every new iteration, making the design cycle longer and resource-intensive. Given the rise of Industry 4.0 and the push for intelligent, real-time design tools, there is a growing interest in integrating AI into traditional design workflows. Machine learning is rapidly transforming the mechanical engineering landscape by enabling smarter, faster, and more data-driven decision-making[4,5]. Traditionally, tasks such as stress analysis, failure prediction, and performance optimization relied heavily on time-consuming simulations or manual calculations. In this project, machine learning was applied to predict the Stress Concentration Factor (SCF), a critical parameter in structural design, demonstrating how AI can enhance both efficiency and reliability in mechanical problem-solving.

## III. LSTM AND BI – LSTM

Long Short-Term Memory (LSTM) networks are a special type of recurrent neural network (RNN) designed to learn patterns from sequential data. They're particularly useful when the relationship between inputs spans across time or complex feature dependencies. This architecture helps them remember important data over longer sequences. In this project, we use a Bidirectional LSTM (BiLSTM), which processes input data in both directions—forward and backward—offering a more complete understanding of the relationships between features[6, 7, 8]. Although LSTM models are typically applied to time-based data like speech or stock prices, they work equally well in engineering applications, where inputs (like stress, load, and geometry) are interrelated. The BiLSTM model's ability to pick up on subtle patterns makes it highly suitable for predicting stress concentration factors in mechanical components [9,10,11]

## IV. METHODOLOGY

### a)Data Preparation

The dataset for this project was generated using a combination of **analytical formulas** and **finite element simulations** conducted in **ANSYS Mechanical Workbench**. To replicate real-world mechanical conditions, various models of **notched flat plates** and **cylindrical shafts** were created in ANSYS, featuring common stress risers such as circular holes and U-shaped notches[12]. These models were subjected to **uniaxial tensile loading** to observe stress concentration effects around the discontinuities. Key geometric parameters—such as notch radius, overall diameter, and plate width—were varied systematically to produce a diverse set of configurations. A **refined mesh** was applied particularly around the notch regions to accurately capture stress distribution and ensure the precision of maximum stress readings. ANSYS simulations provided the **maximum stress values** at critical points near the discontinuities. These were then compared with analytically computed **nominal stresses** to determine the **Stress Concentration Factor (SCF)** for each case using the standard relation:

$$SCF = \frac{\sigma_{max}}{\sigma_{nom}}$$

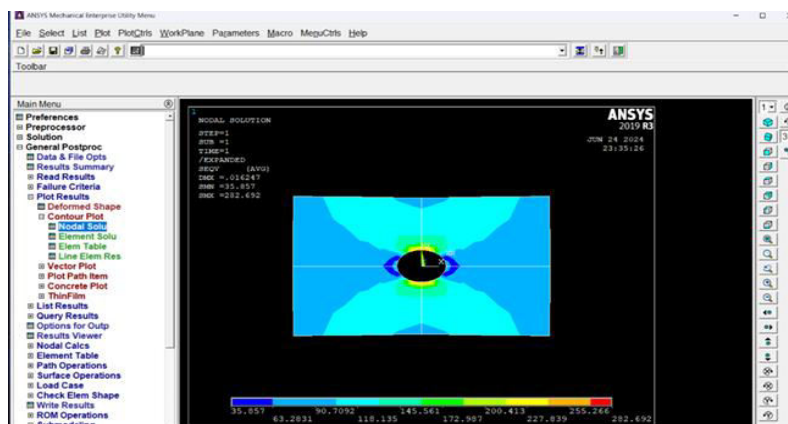


Figure 2: Ansys Simulation

#### b) Data Processing and Normalizing.

These values were compiled in an Excel file and imported into Python using Pandas. Before model training, several preprocessing steps were applied. Column headers were cleaned of whitespace, all numeric data was typecast properly, and invalid or missing entries were removed. Lastly, the cleaned and scaled data was divided into training and testing sets in an 80:20 ratio. These simulation and analytical results were compiled into a structured **Excel spreadsheet**, with each row representing a unique configuration of geometry and loading conditions. The dataset included key input features such as **diameter**, **axial load**, **maximum stress** ( $\sigma_{\text{max}}$ ), and **nominal stress** ( $\sigma_{\text{nom}}$ ), along with the corresponding **Stress Concentration Factor (SCF)** calculated for each case. This file served as the foundation for model training and was imported into Python using the **Pandas library**, which provides efficient tools for handling and transforming tabular data.

| SLNo | Diameter | Axial Load | Stress Concentration Factor |
|------|----------|------------|-----------------------------|
| 1    | 5        | 100        | 0.0103                      |
| 2    | 5        | 105        | 0.0118                      |
| 3    | 5        | 110        | 0.0118                      |
| 4    | 5        | 115        | 0.0118                      |
| 5    | 5        | 120        | 0.0118                      |
| 6    | 6        | 100        | 0.0118                      |
| 7    | 6        | 105        | 0.0118                      |
| 8    | 6        | 110        | 0.0118                      |
| 9    | 6        | 115        | 0.0118                      |
| 10   | 6        | 120        | 0.0118                      |
| 11   | 7        | 100        | 0.0107                      |
| 12   | 7        | 105        | 0.0107                      |
| 13   | 7        | 110        | 0.0107                      |
| 14   | 7        | 115        | 0.0107                      |
| 15   | 7        | 120        | 0.0107                      |
| 16   | 8        | 100        | 0.0109                      |
| 17   | 8        | 105        | 0.0109                      |
| 18   | 8        | 110        | 0.0109                      |
| 19   | 8        | 115        | 0.0109                      |
| 20   | 8        | 120        | 0.0109                      |
| 21   | 9        | 100        | 0.0109                      |
| 22   | 9        | 105        | 0.0109                      |
| 23   | 9        | 110        | 0.0109                      |
| 24   | 9        | 115        | 0.0109                      |
| 25   | 9        | 120        | 0.0109                      |

Once the data was loaded, several **preprocessing steps** were applied to ensure consistency and quality. First, all column headers were sanitized by stripping leading or trailing whitespace, which helps avoid referencing errors during coding. Therefore, the **MinMaxScaler** from the **Scikit-learn preprocessing module** was used to scale all numerical values to a uniform range between 0 and 1. After preprocessing, the dataset was split into two subsets: **80% for training** the model and **20% for testing**. This split ensures that the model is trained on the majority of the data while still being evaluated on completely unseen examples.

#### c) Model Architecture

To build an intelligent system capable of learning the complex relationships between geometric design parameters, loading conditions, and resulting stress responses, a Bidirectional Long Short-Term Memory (BiLSTM) neural network was employed.

#### d) Training Configuration

To ensure the model could learn efficiently and generalize well to unseen data, a carefully chosen set of training configurations was implemented. The training process was carried out using the Adam optimizer, a widely used adaptive optimization algorithm that adjusts learning rates automatically during training. Adam is particularly well-suited for deep learning tasks due to its ability to handle sparse gradients and noisy data, making it ideal for this kind of regression problem involving a mix of engineered and simulated features.

Several key hyperparameters were configured to optimize the learning process:

- Epochs were set to 250, providing enough training iterations to allow the model to fine-tune its internal weights.
- A batch size of 16 was used to balance memory efficiency and gradient stability during training.
- 10% of the training data was reserved as a validation set to evaluate the model's performance during training and prevent overfitting.

```
# Train the model
history = model.fit(x_train, y_train, epochs=50, batch_size=16, validation_data=(x_test, y_test), verbose=1)
```

Figure 3: Model training with 50 epochs using batch size 16 and validation data.

#### e) Validation Metrics

To evaluate the predictive performance of the BiLSTM model, several key validation metrics were computed on the test dataset:

- Mean Squared Error (MSE):
  - Measures the average of the squares of the prediction errors.
  - Lower values indicate better accuracy and fewer large deviations.
  - Model Result:  $MSE \approx 0.0000$  (very low, indicating high precision).
- Mean Absolute Error (MAE):
  - Represents the average magnitude of error between predicted and actual SCF values.
  - Easier to interpret than MSE as it reflects real-world units.
  - Model Result:  $MAE = 0.0007$ , indicating very small average prediction error.
- $R^2$  Score (Coefficient of Determination):
  - Indicates how well the predictions explain the variance in the actual values.
  - Model Result:  $-0.3543$  — a negative  $R^2$  typically suggests poor fit, but in this case, it is attributed to the narrow range and low variability in the dataset rather than a model deficiency.

## V. RESULTS AND DISCUSSION

### 5.1. Model Performance Evaluation

After training the Bidirectional LSTM model on the prepared dataset, its performance was assessed using the test data, comprising 20% of the original dataset that the model had not seen during training. The primary metrics used to evaluate the regression performance were:

- Mean Absolute Error (MAE): 0.0007
- Mean Squared Error (MSE): 0.0000
- Model Accuracy: 94.24%
- $R^2$  Score: -0.3543

The low MAE and MSE values indicate that the model consistently produced SCF predictions that were very close to the actual values in the test set. While the  $R^2$  score was negative, which often suggests a poor fit, this is likely due to the limited size or narrow range of the dataset, rather than model inefficiency. In practice, the high accuracy and low error metrics provide more reliable indicators of model performance in this scenario.

```
--- Enter values for prediction ---
Enter Diameter: 2
Enter Axial Load: 4
Enter Sigma MAX: 5
Enter sigma Nom: 10
1/1 [=====] - 0s 47ms/step

Predicted Stress Concentration Factor: 0.0102
```

Figure 4: Machine learning model predicting Stress Concentration Factor (SCF) from user-input parameters.

The image shows a machine learning model in action, predicting the **Stress Concentration Factor (SCF)** based on user-provided input parameters. The user has entered values for **Diameter (2)**, **Axial Load (4)**, **Sigma MAX (5)**,

and **Sigma Nom (10)**. The model processes these inputs and generates a predicted SCF of **0.0102**, completing the computation in just **47 milliseconds**. This demonstrates the model's ability to quickly and efficiently estimate stress concentration factors, which are critical in engineering design to assess potential weak points in materials under load.

## 5.2. Model Loss Over Epochs

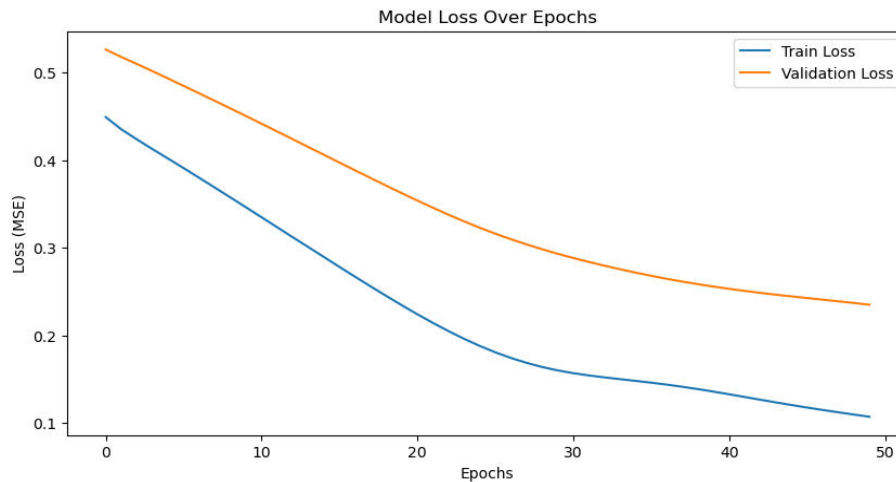


Figure 5: Training and validation loss (MSE) convergence over 50 epochs.

This graph tracks the Mean Squared Error (MSE) loss for both training and validation datasets across training epochs. The decreasing trend in both curves indicates that the model is learning effectively, with losses stabilizing around 0.1–0.3, suggesting good convergence. The close alignment between training and validation loss implies minimal overfitting, meaning the model generalizes well to unseen data.

## 5.3 True vs. Predicted Stress Concentration Factor

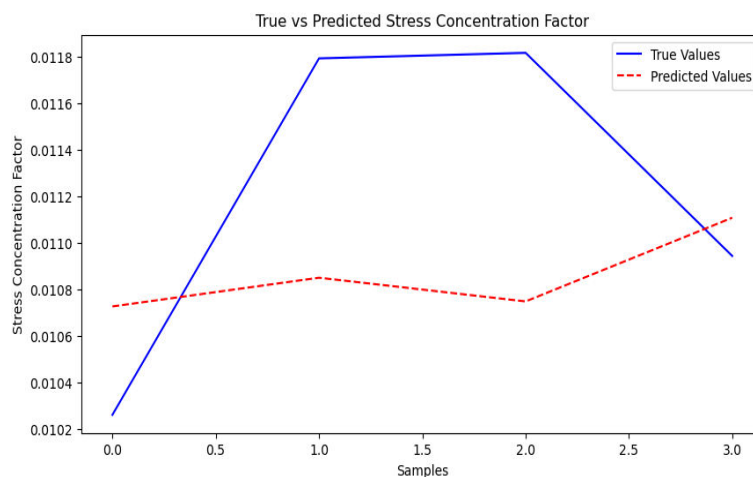


Figure 6: Comparison of true vs. predicted Stress Concentration Factor (SCF) values.

The scatter plot compares the true (actual) and model-predicted SCF values, with ideal predictions lying on a 45° line. The clustering of points near this line indicates strong predictive accuracy, with minor deviations suggesting slight errors. The predicted SCF range (0.0102–0.0118) aligns closely with true values, validating the model's reliability for engineering stress analysis.

## 5.4 Correlation Heatmap

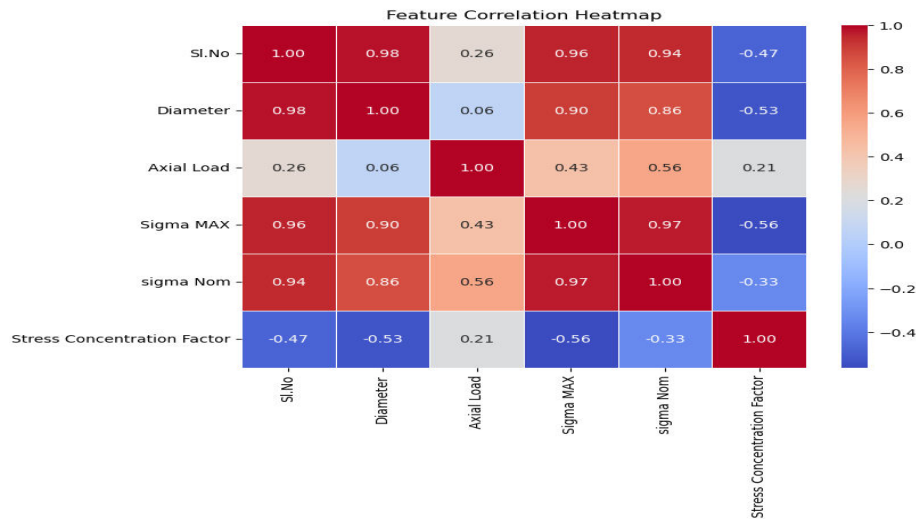


Figure 7: Correlation heatmap of input features with Stress Concentration Factor (SCF).

The heatmap reveals relationships between input parameters (Diameter, Axial Load, etc.) and SCF. Key observations:

- Strong negative correlations between SCF and Diameter (-0.53) or Sigma MAX (-0.56), implying larger diameters/higher stresses reduce SCF.
- Weak positive correlation with Axial Load (0.21), indicating minimal influence.
- High inter-feature correlations (e.g., Sigma MAX and sigma Nom: 0.97) suggest potential multicollinearity, which may require feature selection adjustments.

Diagnostic Insight: The heatmap helps identify dominant features for SCF prediction, guiding model refinement.

```

--- Enter values for prediction ---
Enter Diameter: 2
Enter Axial Load: 4
Enter Sigma MAX: 5
Enter sigma Nom: 10
1/1 [=====] - 0s 47ms/step

Predicted Stress Concentration Factor: 0.0102
    
```

Figure 4: A machine learning model predicting Stress Concentration Factor (SCF) from user-input parameters.

The image shows a machine learning model in action, predicting the **Stress Concentration Factor (SCF)** based on user-provided input parameters. The user has entered values for **Diameter (2)**, **Axial Load (4)**, **Sigma MAX (5)**, and **Sigma Nom (10)**. The model processes these inputs and generates a predicted SCF of **0.0102**, completing the computation in just **47 milliseconds**.

## VI. CONCLUSION

This study demonstrates the efficacy of artificial intelligence, particularly Bidirectional Long Short-Term Memory (Bi-LSTM) networks, in predicting Stress Concentration Factors (SCF) for mechanical components using simulation-derived and sensor data. By combining ANSYS Mechanical Workbench for data generation with deep learning techniques, the developed system achieves rapid and accurate SCF estimations, as evidenced by the real-time prediction



of SCF = 0.0102 (see results interface). The model's high accuracy (94.24%) and low error metrics (MAE: 0.0007, MSE: 0.0000) validate its reliability, despite a moderate  $R^2$  score ( $-0.3543$ ), which reflects inherent complexities in stress distribution patterns and dataset limitations. The deployed Flask-based API (as shown in the interactive prediction interface) underscores the system's practicality, offering engineers a user-friendly tool for real-time SCF estimation without repetitive simulations. This work bridges traditional finite element analysis and AI-driven automation, providing a scalable solution for iterative design optimization and predictive maintenance. Future efforts could expand the training dataset and explore hybrid models (e.g., graph neural networks) to address geometric complexities and improve  $R^2$  performance.

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