

## ✅ Scaling, Encoding & Feature Creation

### 🎯 Aim

Apply **scaling** (Min-Max, Standardization) and **encoding** (One-Hot, Label) to numerical and categorical features.

Create a **new feature** by combining or transforming existing columns.

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### 📌 Overview

This project demonstrates the **preprocessing steps** required before building a machine learning model. It covers:

- Handling **numerical** and **categorical** data
  - Applying **scaling techniques**
  - Performing **encoding methods**
  - Creating **new features** through transformation or combination
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### 🧩 Problem Statement

Raw datasets contain numerical and categorical values in different formats. Without preprocessing:

- Machine learning models may misinterpret the data
- Feature scales may affect performance
- Categorical columns may be unreadable for algorithms

This project solves these issues through structured preprocessing.

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### 🔧 Tools and Technologies

- **Python**
  - **Pandas** – Data manipulation
  - **NumPy** – Numerical operations
  - **Scikit-learn** – Scaling & Encoding
  - **Jupyter Notebook / VS Code** (optional)
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### 🔧 Methods Used

### ✓ 1. Scaling (Numerical Features)

- Min-Max Scaling
- Standardization (Z-score)

### ✓ 2. Encoding (Categorical Features)

- Label Encoding
- One-Hot Encoding

### ✓ 3. Feature Engineering

- Create a new column by combining or transforming existing ones
    - Example:  $\text{Total\_Score} = \text{Marks1} + \text{Marks2}$
    - Example:  $\text{Age\_Group} = \text{Age} // 10 * 10$
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### 💡 Key Insights

- ✓ Scaling brings all numerical values to a comparable range
  - ✓ Encoding helps convert categories into machine-readable format
  - ✓ New feature creation improves data richness and prediction power
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### ✓ Results & Conclusion

- All numerical features are **scaled properly**
- Categorical values are **encoded correctly**
- A **new feature** is created using transformation
- Data is now ready for **model training or EDA**