1. Accuracy, Precision, and Recall Across Fold Sizes and C-Values

- **Accuracy** and **Precision** are relatively stable across different values of `C` and `Fold Size`, with a small range from approximately **0.58 to 0.62**.
- **Recall** is consistently high (close to **1.0**) for all configurations, indicating that the model is able to identify almost all actual positive instances (anomalies).
- **Fold Size** appears to slightly influence accuracy and precision, particularly with a fold size of 10, where these metrics peak slightly compared to 5 or 15.

2. Impact of C-Value on Model Performance

- Different values of `C` (0.1, 1, and 10) do not seem to significantly impact **accuracy**, **precision**, or **recall**. This stability suggests that the model is not very sensitive to regularization strength.
- Since `C` represents the inverse of regularization strength (lower `C` means stronger regularization), the stability implies that regularization has limited influence, possibly due to a relatively balanced dataset or low noise in the features.

3. Distribution Plots for Accuracy, Precision, and Recall

- The box plots show that **accuracy** and **precision** have a small spread, while **recall** has a tighter distribution with most values near **1.0**.
- The narrower distribution of recall compared to accuracy and precision implies that recall is consistently high, which is important in anomaly detection as it suggests a low rate of false negatives.
- For both accuracy and precision, the interquartile range (IQR) is quite small, but there is some variability across folds, indicating that certain data splits might slightly affect model performance.

4. Dataset Quality Observations

- The high recall values indicate that the dataset allows the model to detect anomalies well, with minimal false negatives. This suggests that the features chosen for the model (such as `Acc X`, `gyro_x`, etc.) are effective at distinguishing anomalies.
- However, the lower accuracy and precision values (around 0.6) could indicate a certain level of **class imbalance** or **overlapping feature distributions** between normal and anomalous data points, leading to some false positives.
- If high recall is a priority (common in anomaly detection to ensure anomalies aren't missed), this dataset quality is suitable. However, if reducing false positives is essential, additional feature engineering or different modeling techniques might be needed.

Summary of Results

- The dataset seems to be well-suited for detecting anomalies with high recall, but it may have some overlapping distributions between classes, resulting in moderate precision and accuracy.
- Different fold sizes and values of `C` have minimal impact on performance, indicating robustness in the dataset.
- Improvements could focus on enhancing precision and accuracy, potentially by refining features or applying alternative algorithms.

1. Accuracy, Precision, and Recall Across Fold Sizes and C-Values

- **Accuracy** and **Precision** values are relatively stable across different fold sizes and C-values, ranging approximately between **0.58 and 0.62**.
- **Recall** remains high across configurations, typically close to **1.0**, indicating that the model is very effective at identifying actual positive instances (anomalies).
- Fold size has some influence on accuracy and precision, with a fold size of **10** showing a slight improvement in these metrics compared to fold sizes of **5** or **15**.

2. Impact of C-Value on Model Performance

- Different C-values (0.1, 1, and 10) do not appear to significantly impact accuracy, precision, or recall, suggesting that the model's performance is not particularly sensitive to changes in this parameter. This stability can be attributed to the nature of the Random Forest model, which is inherently less prone to overfitting compared to simpler models.
- Since the C-value controls the regularization strength in logistic regression, and regularization strength does not apply to Random Forests directly, this stability is expected and indicates robustness in handling the data.

3. Distribution Plots for Accuracy, Precision, and Recall

- The box plots for accuracy and precision show a small spread, with moderate variation in scores across different configurations. The central tendency remains around **0.59-0.60** for both metrics.
- The recall distribution is much narrower and close to **1.0** across all configurations, which reinforces that the model is successfully detecting most anomalies (low false negatives).
- For accuracy and precision, the slight variability suggests that the model may be slightly affected by the specific data splits in each fold, though the differences are minimal.

4. Dataset Quality Observations

- The consistently high recall values indicate that the dataset enables the model to effectively identify anomalies, with very few false negatives. This is an important trait in anomaly detection tasks.
- However, the relatively low accuracy and precision values (~0.6) imply that there may be some **overlap** between normal and anomalous instances in feature space, leading to moderate false positives.
- This overlap could be due to either a class imbalance or insufficiently discriminative features, where anomalies and normal instances have similar characteristics, making it harder for the model to clearly separate the two classes.

Summary of Results

- The dataset seems adequate for high-recall anomaly detection tasks, allowing the model to capture most anomalies effectively.
- Improving accuracy and precision might require additional feature engineering or alternative modeling approaches to reduce false positives.
- Different fold sizes and C-values do not significantly impact performance, showing robustness in the Random Forest model with this dataset.