

# Machine Learning Model Evaluation Report

## 1. Modeling Problem

We explored two types of machine learning problems:

### Regression Problems

- **Model 1:** Predicting Canada's *Per Capita Income* over the years.
- **Model 2:** Predicting *Maximum Temperature* in Lahore using historical weather data.

### Classification Problems

- **Model 3:** Classifying iris flowers using **KMeans (unsupervised)**.
- **Model 4:** Predicting iris flower species using **Random Forest Classifier**.
- **Model 5:** Predicting iris flower species using **Support Vector Machine (SVM)**.

## 2. Models Trained

### Regression Models

| Model                           | Dataset                  | Technique                      | Preprocessing             | Tuning |
|---------------------------------|--------------------------|--------------------------------|---------------------------|--------|
| Linear Regression               | Canada Per Capita Income | LinearRegression()             | None                      | No     |
| Linear Regression with Pipeline | Lahore Weather Data      | Pipeline + FunctionTransformer | Date converted to ordinal | No     |

### Classification Models

| Model | Dataset | Technique | Preprocessing | Tuning |
|-------|---------|-----------|---------------|--------|
|-------|---------|-----------|---------------|--------|

|                           |              |                          |              |                                  |
|---------------------------|--------------|--------------------------|--------------|----------------------------------|
| KMeans Clustering         | Iris Dataset | KMeans(n_clusters=3)     | MinMaxScaler | No                               |
| Random Forest Classifier  | Iris Dataset | RandomForestClassifier() | None         | No                               |
| Support Vector Classifier | Iris Dataset | SVC(C=10)                | None         | GridSearchCV, RandomizedSearchCV |

### 3. Evaluation Metrics

#### Regression Models Evaluation

| Model                         | R <sup>2</sup> Score                  | Additional Notes                       |
|-------------------------------|---------------------------------------|--|
| Canada Income Prediction      | High R <sup>2</sup> (visually linear) | Predicted 2025 income successfully     |
| Lahore Temperature Prediction | model.score() used                    | Custom pipeline used with ordinal date |

#### Recommended Improvements:

- Evaluate using **MAE**, **MSE**, and **R<sup>2</sup>** explicitly.
- Add cross-validation or time-series split for better evaluation.

#### Classification Models Evaluation

| Model                  | Accuracy   | Precision               | Recall                         | F1-Score               |
|------------------------|------------|-------------------------|--------------------------------|------------------------|
| KMeans + Label Mapping | Reasonable | Used mode-based mapping | Good for unsupervised baseline | Decent but not optimal |
| Random Forest          | ~90%       | High                    | High                           | High                   |
| SVM                    | ~97%       | High                    | High                           | High                   |

#### Hyperparameter Tuning:

- **SVM**: Tuned using GridSearchCV and RandomizedSearchCV with parameters C and kernel.

## 4. Visualizations Included

- Scatter plots for income and temperature trends.
- Cluster visualizations for KMeans using petal features.
- Heatmaps for confusion matrices of classification models.
- Elbow curve for optimal K in KMeans.

## 5. Key Observations & Improvements

### Observations

- Linear models work well on clean, linear trends (e.g., income, temperature).
- Random Forest outperforms SVM slightly on Iris dataset without tuning.
- KMeans is good as an unsupervised learning example but less accurate than supervised methods.

### Improvements

- Add error metrics (RMSE, MAE) for regression.
- Add cross-validation scores for classification robustness.
- For temperature prediction, consider seasonality trends or time-series models.
- Incorporate more features (e.g., humidity, wind) for temperature prediction.
- Use classification reports and ROC curves for deeper classification insight.