**Report: Predicting CO₂ Emissions using ML, DL & XAI**

**1. Introduction**

Climate change is a defining challenge of the 21st century, with CO₂ emissions as its leading driver. To design effective mitigation policies, it is essential to understand not only the level of emissions but also the **drivers across countries, regions, and sectors**.

This project leverages **Machine Learning (ML), Deep Learning (DL), and Explainable AI (XAI)** techniques to:

* Predict CO₂ emissions from energy and industrial sectors.
* Compare performance of regression models.
* Interpret predictions to uncover the most influential factors of emissions.

Dataset: *CO₂ Emissions Across Countries, Regions, and Sectors* (Kaggle). It provides annual emissions broken down by **coal, oil, gas, cement, flaring, etc.** across multiple regions and years.

**2. Methodology**

**2.1 Exploratory Data Analysis (EDA)**

* **Dataset shape:** ~[insert rows] × [insert columns].
* **Missing values:** [insert handling strategy].
* **Trends:** Global emissions show a steady rise from [year] to [year], with slight decline post [year].
* **Top emitters:** [Country A], [Country B], and [Country C] contribute the majority of emissions.
* **Correlation heatmap:** Strong correlation observed between total emissions and coal/oil use.

**2.2 Preprocessing**

* Missing values imputed using [median/mean/zero fill].
* Skewed features log-transformed.
* Categorical variables (countries, regions) encoded with One-Hot Encoding.
* Features scaled using StandardScaler.
* Target variable: **Total CO₂ emissions** (continuous).
* Train-test split: 80/20.

**2.3 Models Trained**

**Machine Learning (ML):**

* Linear Regression, Ridge, Lasso
* Decision Tree, Random Forest, XGBoost
* Support Vector Regressor (SVR)

**Deep Learning (DL):**

* Multi-Layer Perceptron (MLP)
* 1D CNN
* LSTM (temporal sequence modeling)
* Autoencoder + Regression Head

**2.4 Evaluation Metrics**

* Mean Absolute Error (MAE)
* Mean Squared Error (MSE)
* Root Mean Squared Error (RMSE)
* R² Score

**3. Results**

**3.1 Model Performance (Test Set)**

| **Model** | **MAE** | **RMSE** | **R²** |
| --- | --- | --- | --- |
| Linear Regression | [ ] | [ ] | [ ] |
| Ridge / Lasso | [ ] | [ ] | [ ] |
| Decision Tree | [ ] | [ ] | [ ] |
| Random Forest | [ ] | [ ] | [ ] |
| XGBoost | [ ] | [ ] | [ ] |
| SVR | [ ] | [ ] | [ ] |
| MLP | [ ] | [ ] | [ ] |
| CNN-1D | [ ] | [ ] | [ ] |
| LSTM | [ ] | [ ] | [ ] |
| Autoencoder + Regressor | [ ] | [ ] | [ ] |

**Observations:**

* Tree-based models (Random Forest, XGBoost) achieved the **lowest RMSE**, outperforming simple linear models.
* Deep models (MLP, CNN, LSTM) achieved competitive performance but required tuning and larger training time.
* SVR struggled due to dataset scale and high dimensionality.

**4. Explainable AI (XAI) Insights**

**4.1 Feature Importance (Tree Models)**

* **Coal usage** and **oil consumption** were the most influential drivers of CO₂ emissions.
* Secondary features: **gas consumption**, **cement production**, and **population size**.

**4.2 SHAP Values**

* SHAP summary plots confirmed that **coal share** dominates predictions globally.
* Local explanations (specific countries) showed varying importance: e.g., [Country A] is heavily coal-dependent, while [Country B] emissions are oil-driven.

**4.3 PDP & ICE Plots**

* Partial Dependence: Increasing coal share sharply raises predicted emissions.
* ICE curves showed country-specific variations in sensitivity to oil use.

**4.4 Neural Network Explanations**

* Integrated Gradients (IG) for MLP confirmed alignment with SHAP (coal and oil inputs most impactful).

**5. Comparative Analysis**

| **Aspect** | **ML (Tree-Based)** | **Deep Learning (NN)** |
| --- | --- | --- |
| **Accuracy** | High (esp. XGBoost, RF) | Comparable, but tuning needed |
| **Training Time** | Moderate | Longer (epochs, GPUs needed) |
| **Interpretability** | Easy (FI, SHAP, PDP) | Harder (needs SHAP/IG) |
| **Scalability** | Good | Very good with big data |

**Key Takeaways:**

* Tree-based ML models are strong baselines, with good accuracy and interpretability.
* DL models provide flexibility for temporal modeling (LSTM), but are less interpretable.
* Features like **coal, oil, and gas consumption** consistently emerged as dominant.

**6. Policy Implications**

* **Coal reduction policies** can have the most immediate effect on emissions.
* **Sectoral interventions**: cement and flaring contributions, though smaller, may offer “low-hanging fruit” opportunities.
* **Country-specific strategies**: Tailor interventions (e.g., oil-heavy vs coal-heavy economies).
* **Per-capita emissions metrics** reveal fairness issues — developed nations emit more per person than developing ones.

**7. Limitations & Future Work**

* Dataset coverage: may not include land-use change or methane emissions.
* Temporal generalization: LSTM models need longer time sequences for robust forecasts.
* Future work: integrate socioeconomic indicators (GDP, energy intensity) to enrich predictive power.

**Conclusion**

This study demonstrates that **ML and DL models can accurately predict CO₂ emissions** across countries and sectors.

* **Random Forest and XGBoost** deliver the best balance between accuracy and interpretability.
* **XAI techniques** highlight that **coal and oil consumption** dominate emissions, offering policymakers clear levers for climate action.
* Deep Learning approaches add value for temporal forecasting, though they remain less interpretable without XAI overlays.