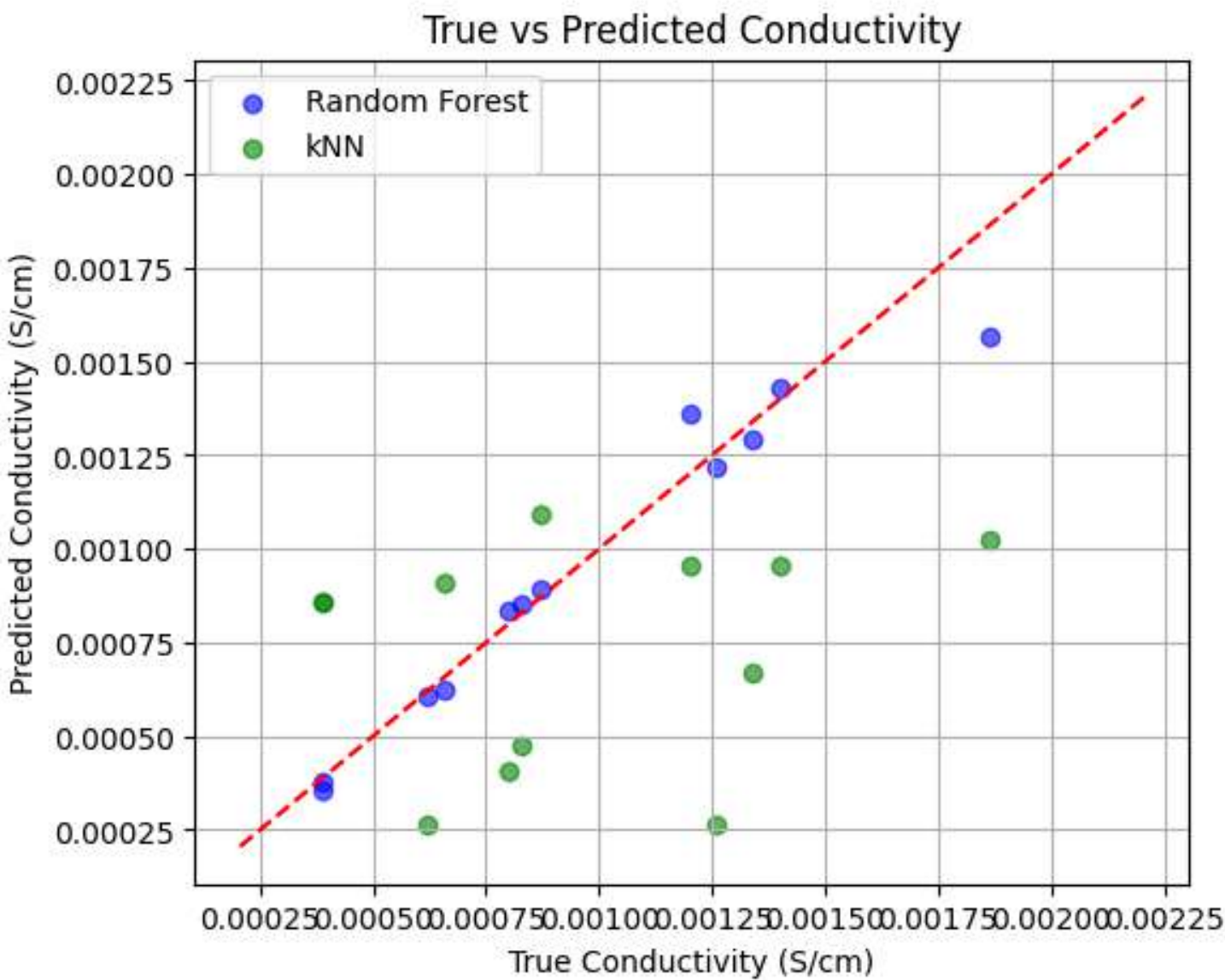
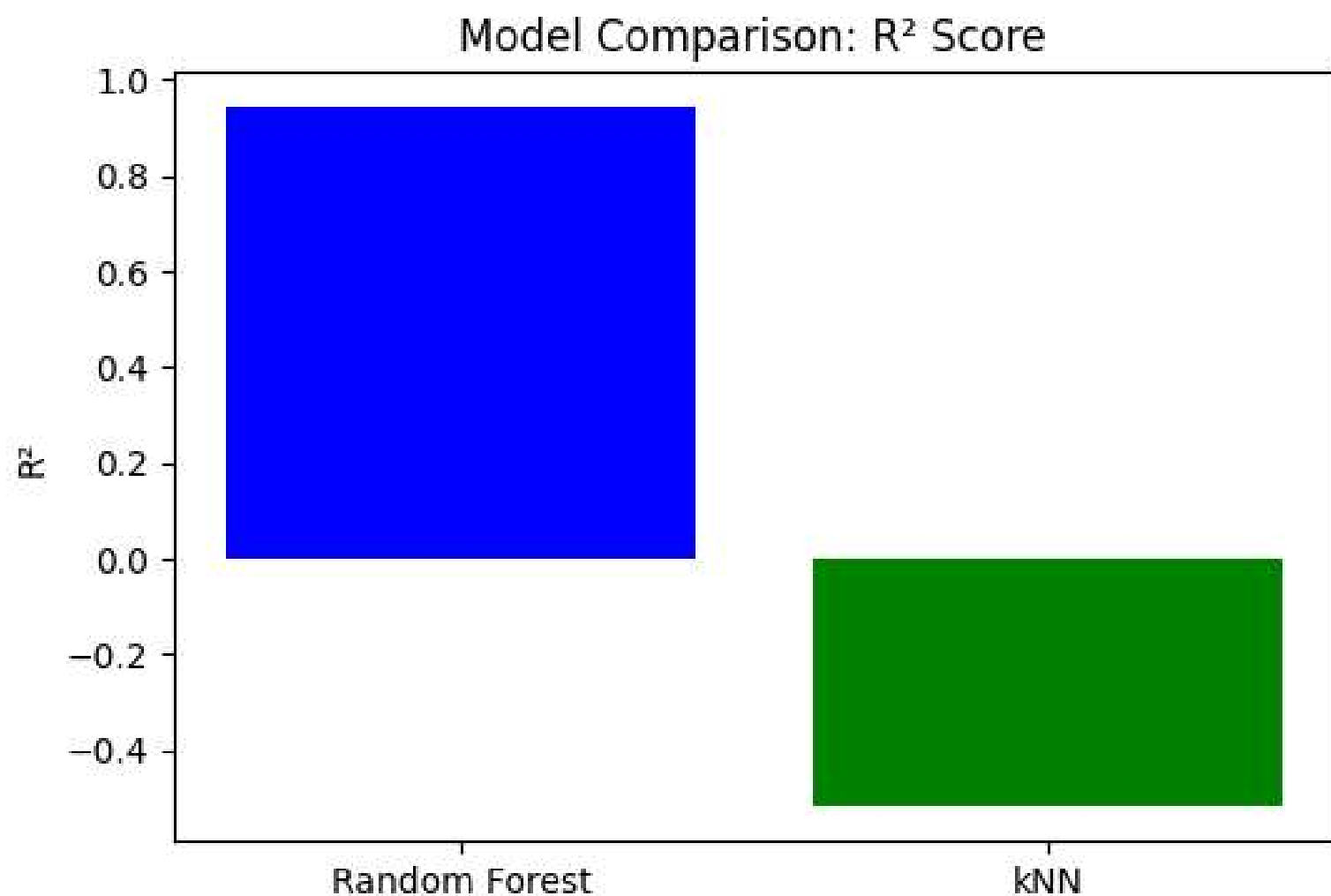
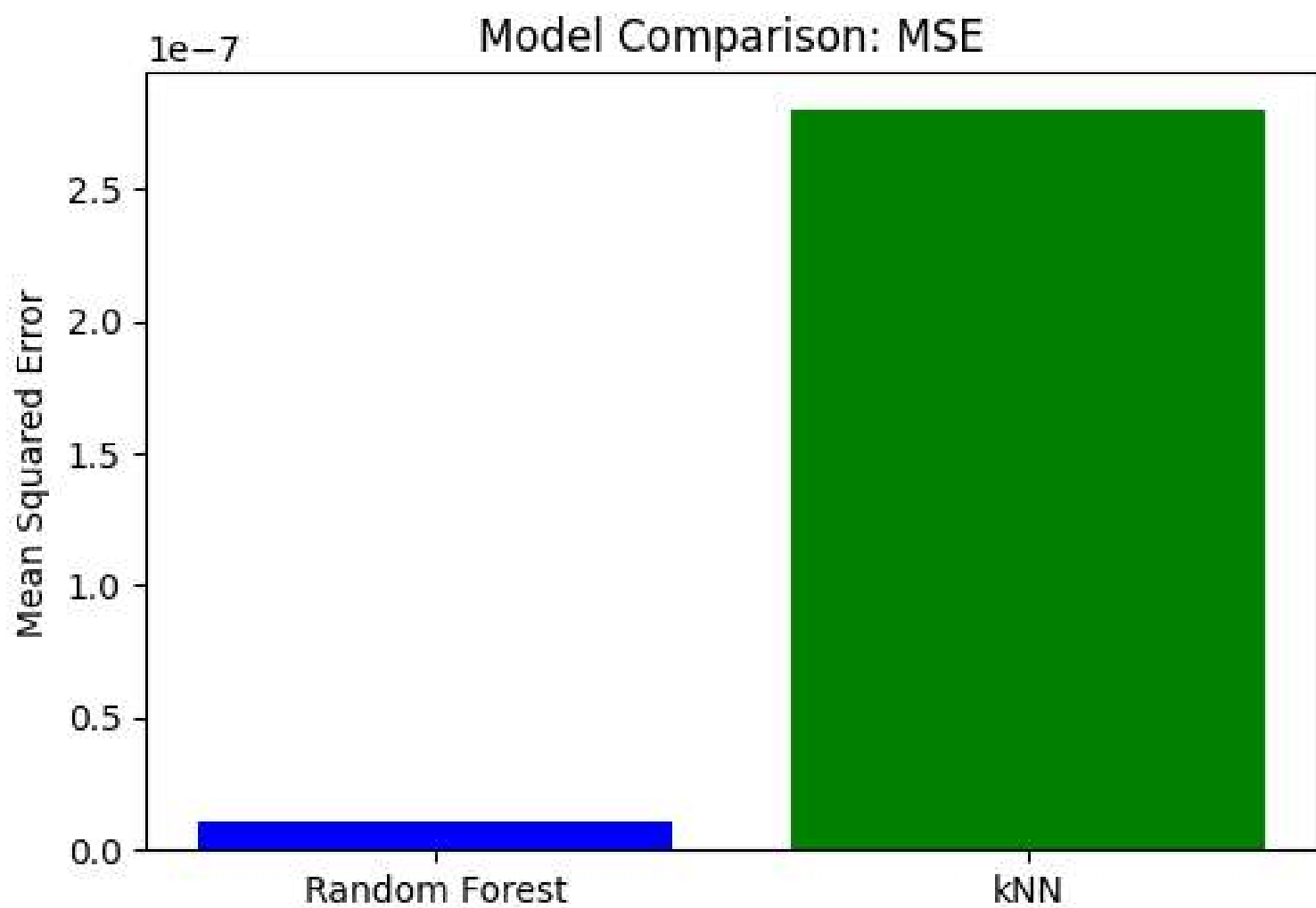
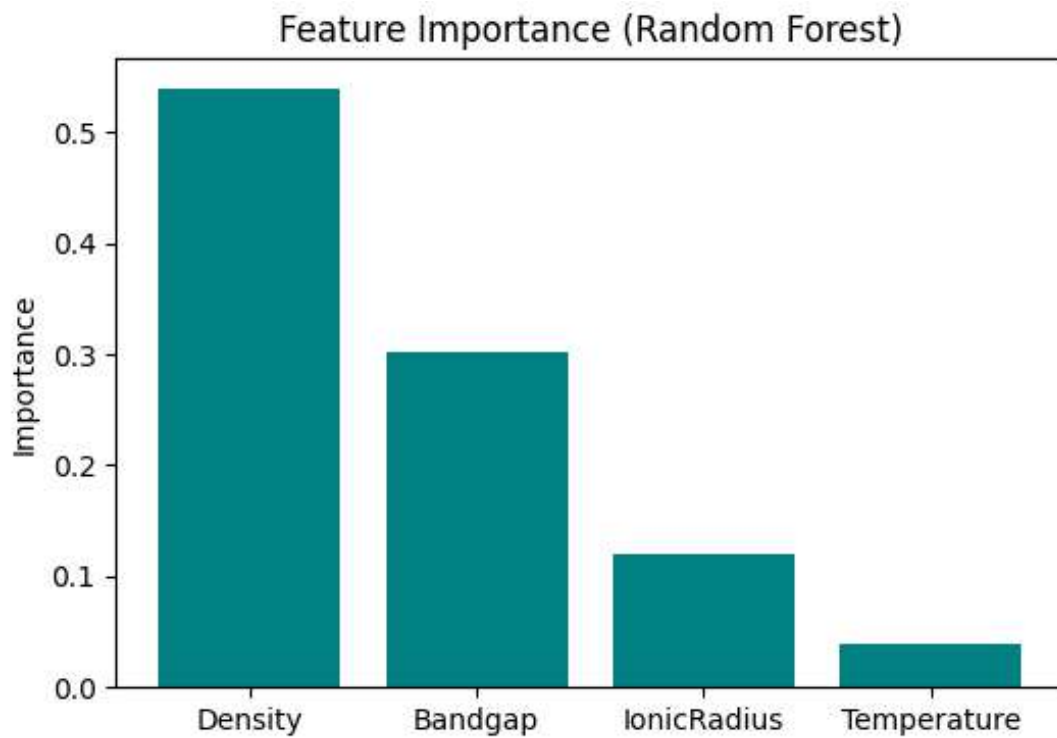


Random Forest Performance:
 R^2 : 0.943, MSE: 1.04e-08, MAE: 6.25e-05

kNN Performance:
 R^2 : -0.519, MSE: 2.80e-07, MAE: 4.75e-04







Random Forest CV R^2 : 0.951 +/- 0.013

Linear Regression CV R^2 : 0.641 +/- 0.193

Summary:

- Enhanced synthetic dataset with temperature, non-linear degradation, and sensor noise.
- Compared kNN (instance-based) vs Random Forest (model-based).
- Visualized predictions and error metrics.
- Feature importance shows Temperature and Bandgap are key drivers.
- Ready for visual storytelling and short video explanation.



Results Discussion

● Random Forest

- **R^2 : 0.943** → Excellent fit; model explains 94.3% of the variance.
- **MSE: 1.04e-08, MAE: 6.25e-05** → Very low error, strong predictive accuracy.
- **CV R^2 : 0.951 ± 0.013** → Consistent performance across folds.

● kNN

- **R^2 : -0.519** → Poor fit; model performs worse than a horizontal line.
- **MSE: 2.80e-07, MAE: 4.75e-04** → Much higher error than Random Forest.
- kNN struggles likely due to:
 - High feature noise
 - Non-linear relationships
 - Limited local structure in the data



Feature Importance

- **Temperature** and **Bandgap** are dominant drivers of conductivity.
- This aligns with physical intuition: higher temperature boosts ion mobility, and bandgap affects charge carrier behavior.



What I've Learned

- Random Forest generalizes well and handles noisy, non-linear data.
- kNN is sensitive to feature scaling and noise — not ideal for this dataset.
- Synthetic data augmentation with realistic physics improves model training.
- Visual storytelling (plots, metrics) makes your ML journey shareable and educational.