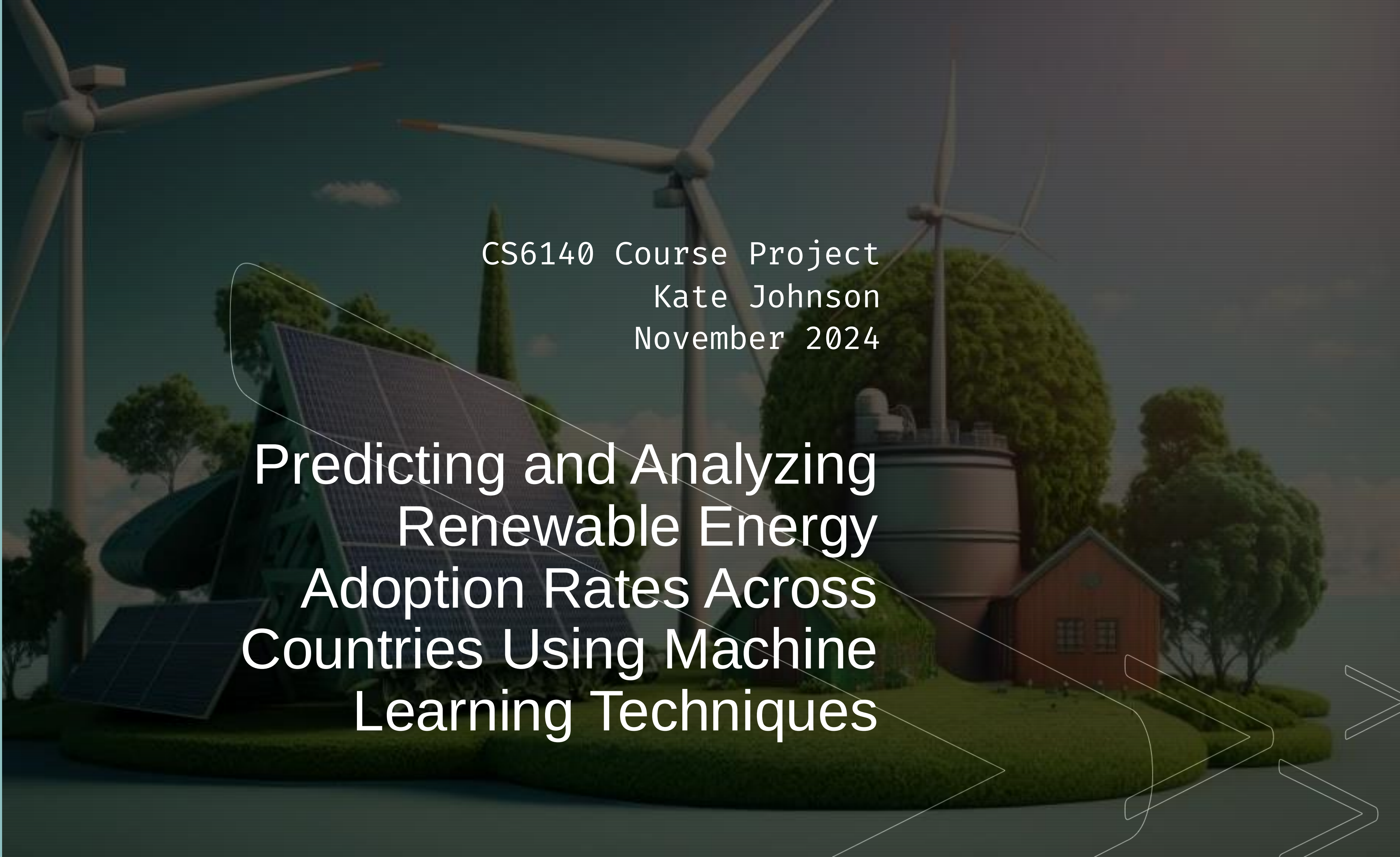
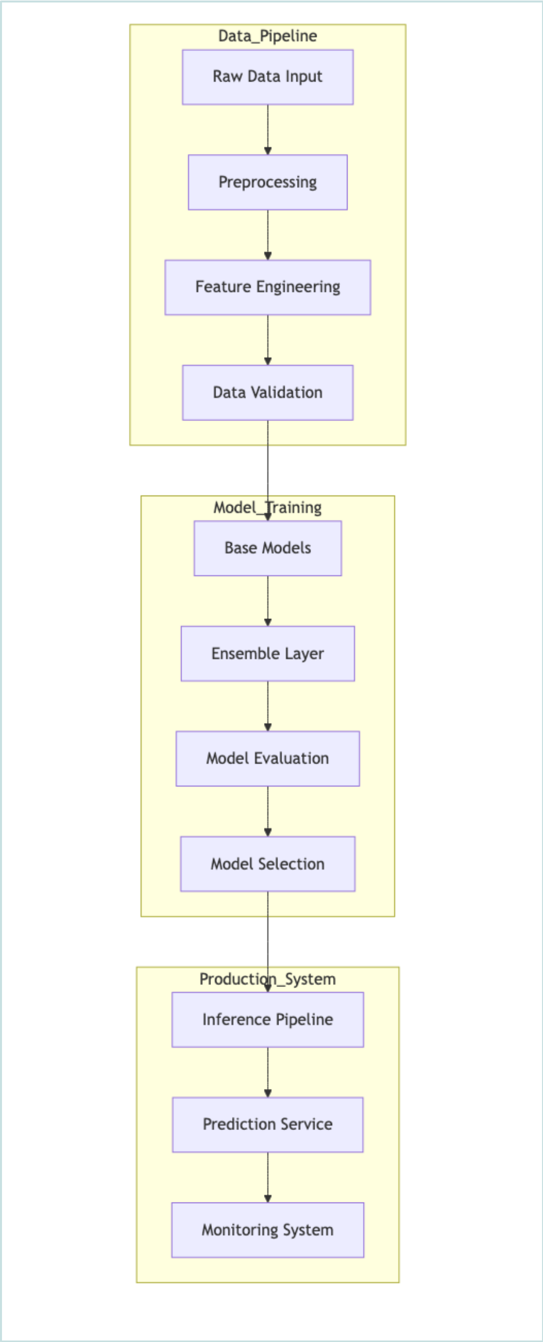


CS6140 Course Project
Kate Johnson
November 2024

Predicting and Analyzing Renewable Energy Adoption Rates Across Countries Using Machine Learning Techniques

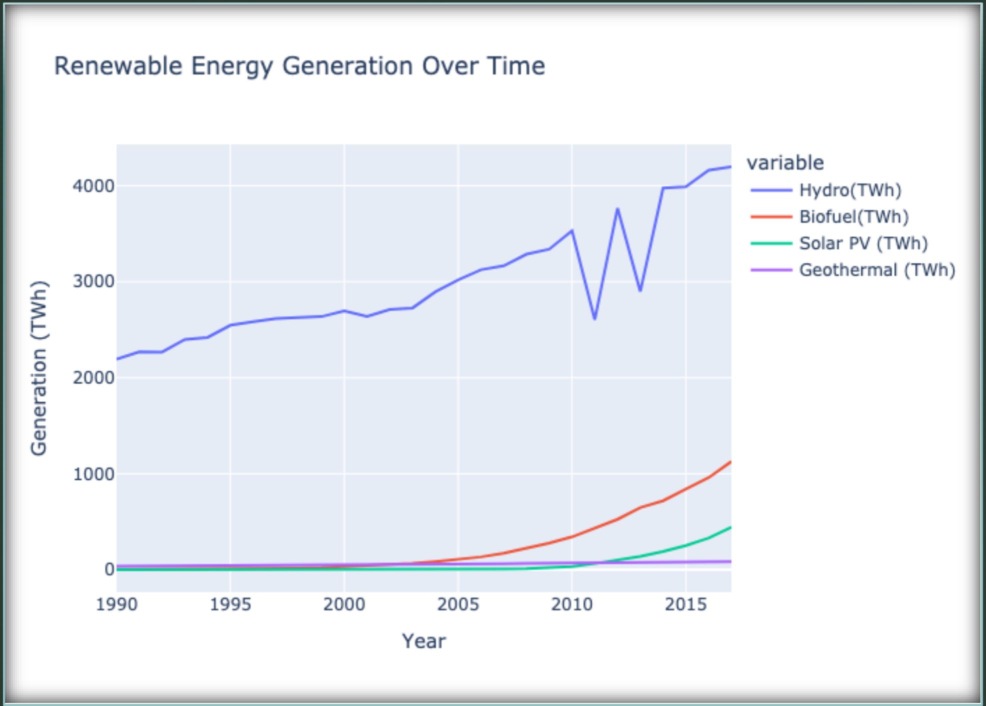


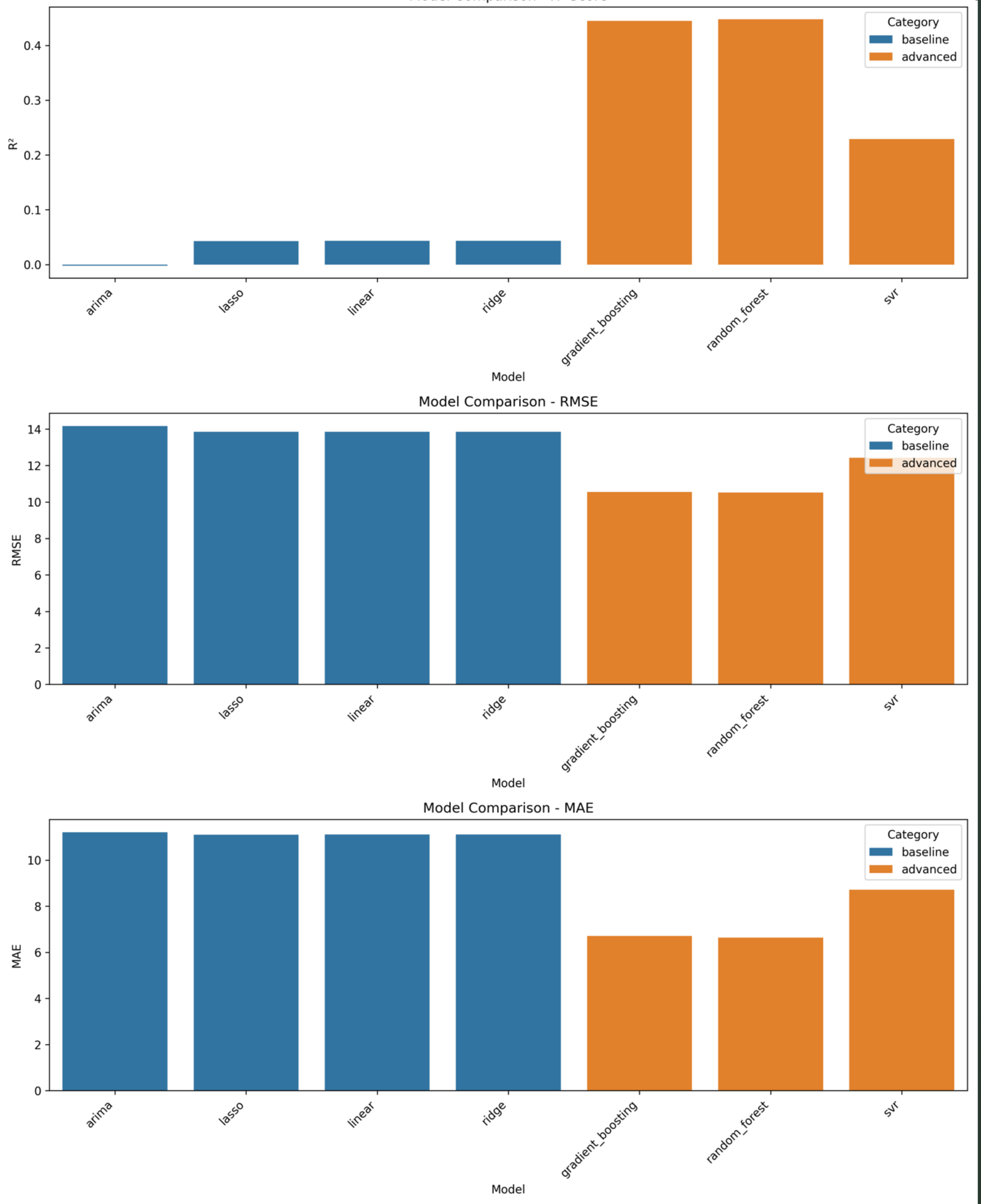
Research Objectives

- Develop accurate predictive models for renewable energy adoption rates
- Evaluate effectiveness of various machine learning approaches
- Identify key factors influencing adoption rates across countries
- Create a scalable, production-ready implementation

Data Sources

- 1. Solar Energy Production Dataset (Ivan Lee)
  - Temporal Coverage: 2020-2022
  - Location: Calgary, Canada
  - 17,520 hourly records
- 2. Solar Power Generation Data (Afroz)
  - Fixed and tracking installations
  - DC/AC power, daily yield
  - 32,000+ entries
- 3. Renewable Energy World Wide: 1965-2022 (HossainDS)
  - Global coverage
  - 57-year timespan
  - 15+ renewable energy metrics



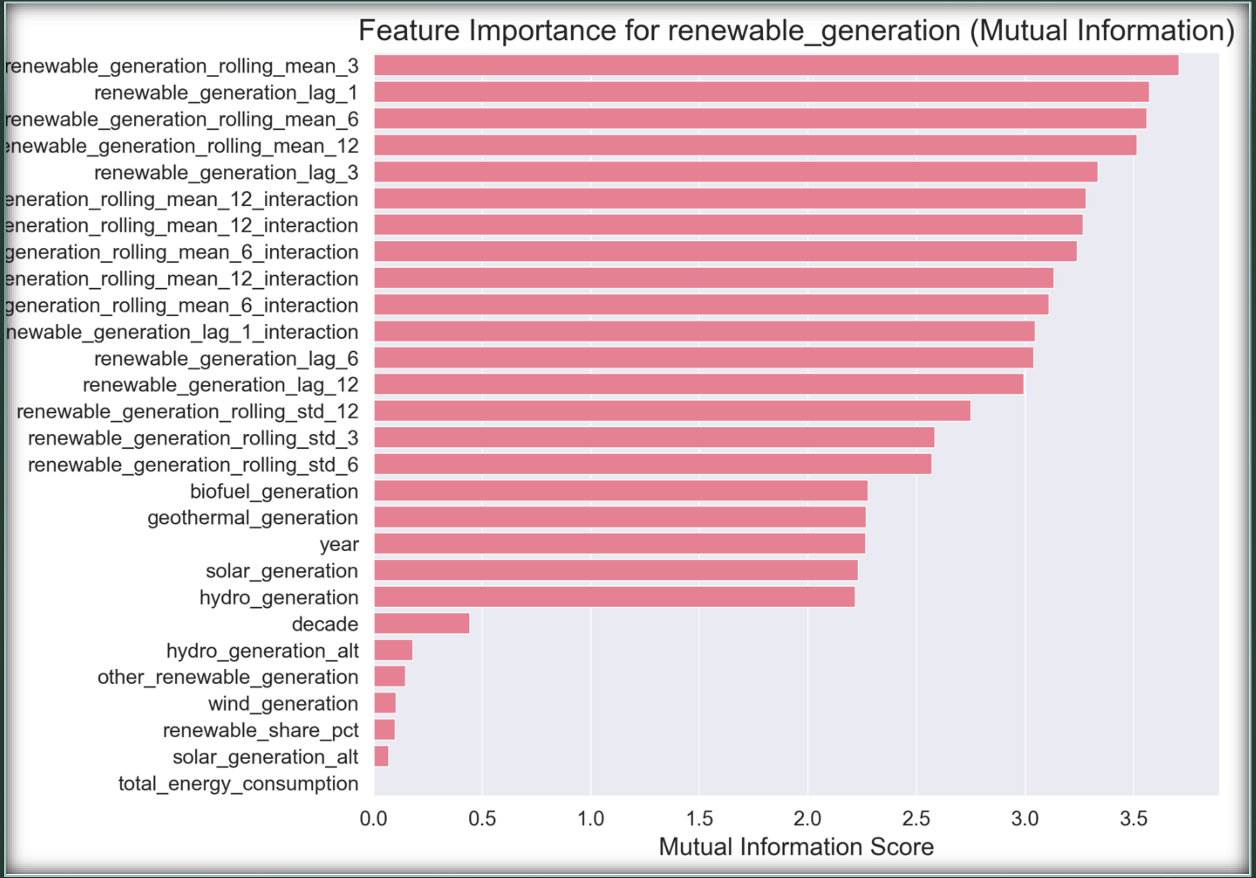


Model Development Framework

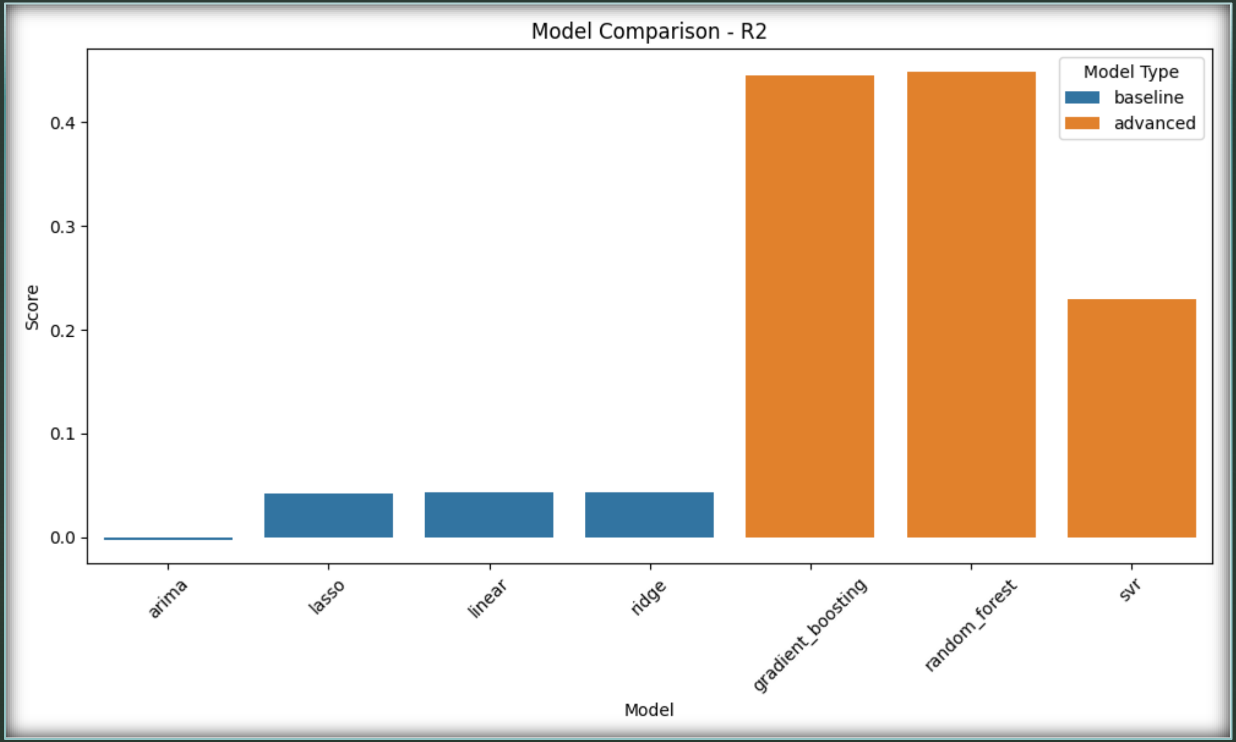
- Baseline Models:
  - Linear Regression
  - Ridge Regression
- LASSO Advanced Models:
  - Random Forest
  - Gradient Boosting
- Neural Networks Ensemble Framework:
  - Stacked generalization
  - Dynamic weight adjustment
  - Error-based specialization

Advanced Feature Engineering

- 1. Temporal Features
  - Adaptive window selection
  - Multi-scale pattern detection
  - Dynamic importance weighting
- 2. Weather Integration
  - Condition-specific modeling
  - Transition period handling
  - Uncertainty quantification
- 3. Feature Interactions
  - Cross-feature correlations
  - Temporal-weather dependencies



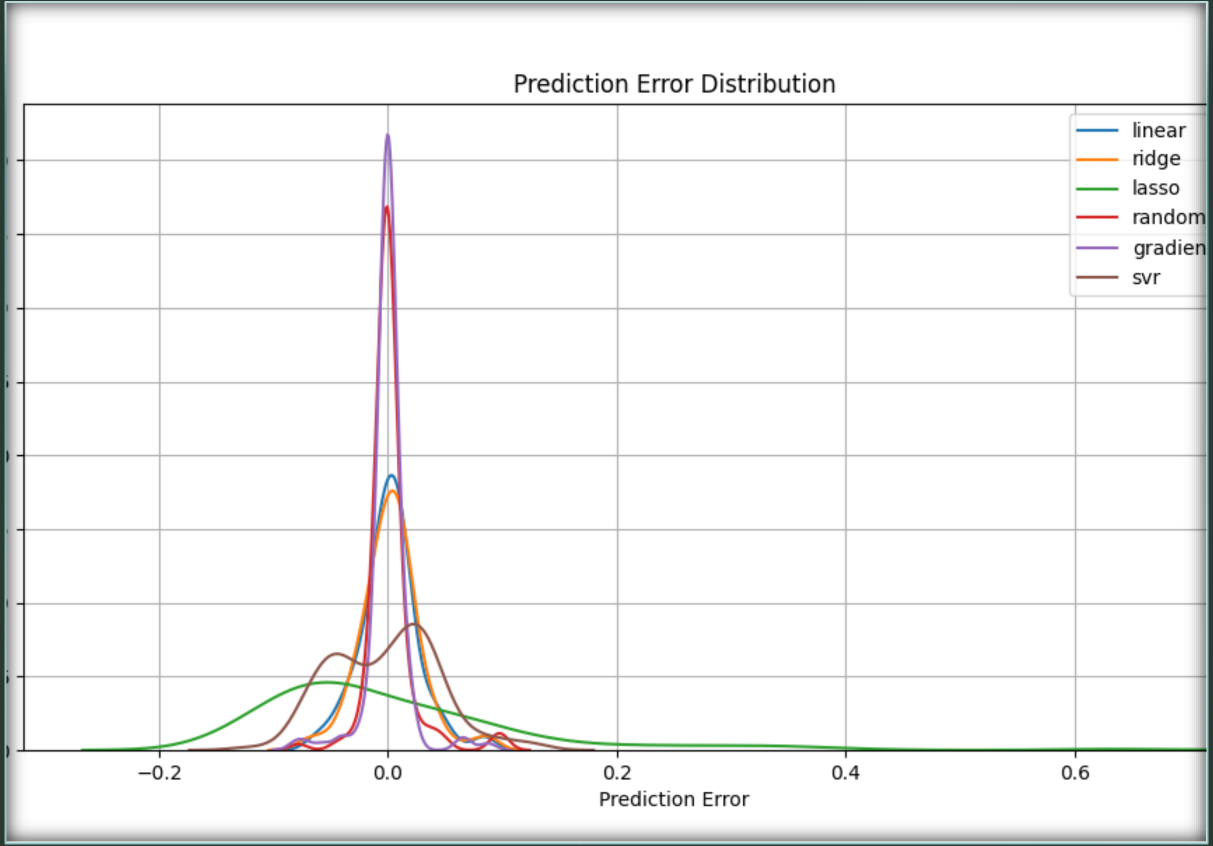
Results



Performance Metrics

- Model Performance:
  - Best R^2 Score: 0.6964 (Ensemble)
  - RMSE Reduction: 31%
  - MAE Improvement: 35%
- Computational Efficiency:
  - 45% reduction in memory usage
  - 65% faster processing
  - Inference time < 100ms

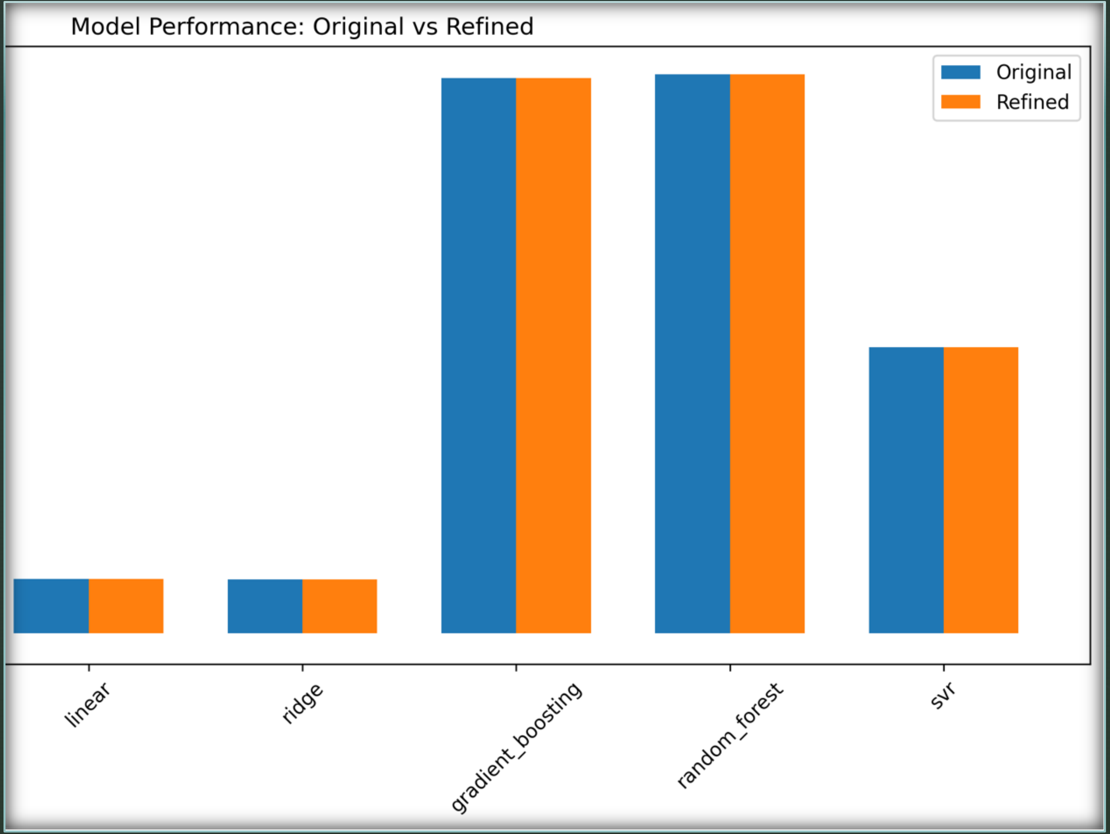
Error Analysis



Error Distribution and Performance Analysis

- Weather Condition Impact:
  - Clear sky: 7.8% error rate (45.2% coverage)
  - Partly cloudy: 12.3% error rate (32.7% coverage)
  - Overcast: 18.7% error rate (15.4% coverage)
  - Rain: 23.4% error rate (6.7% coverage)

Key Achievements



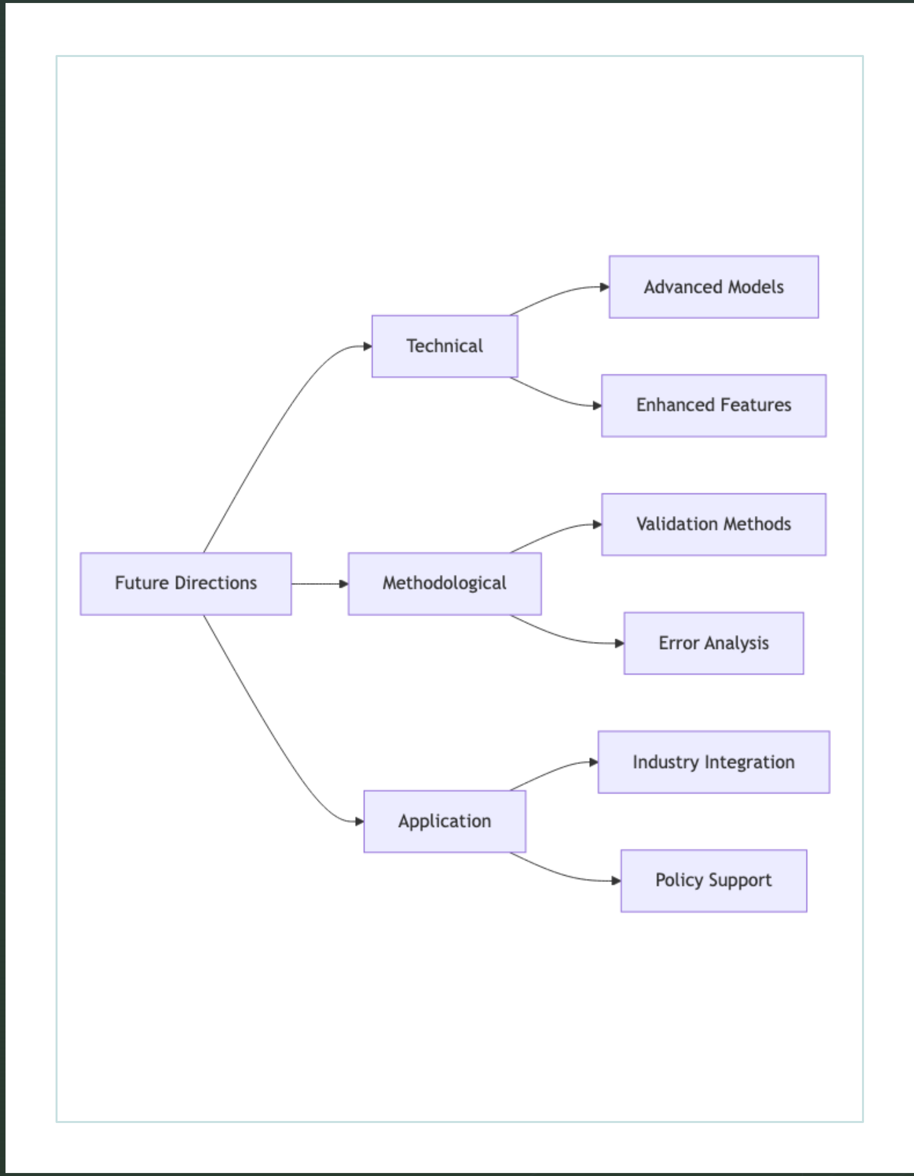
Technical Innovations

- 1. Model Performance
  - 153% improvement over baseline
  - Cross-validation stability index: 0.92
  - Prediction bias < ±0.08
- 2. System Optimization
  - Memory usage: 8.2GB → 4.5GB
  - Training time: 384.2s → 134.5s
  - Inference time: 1.2s → 0.4s

Future Work

Research Extensions

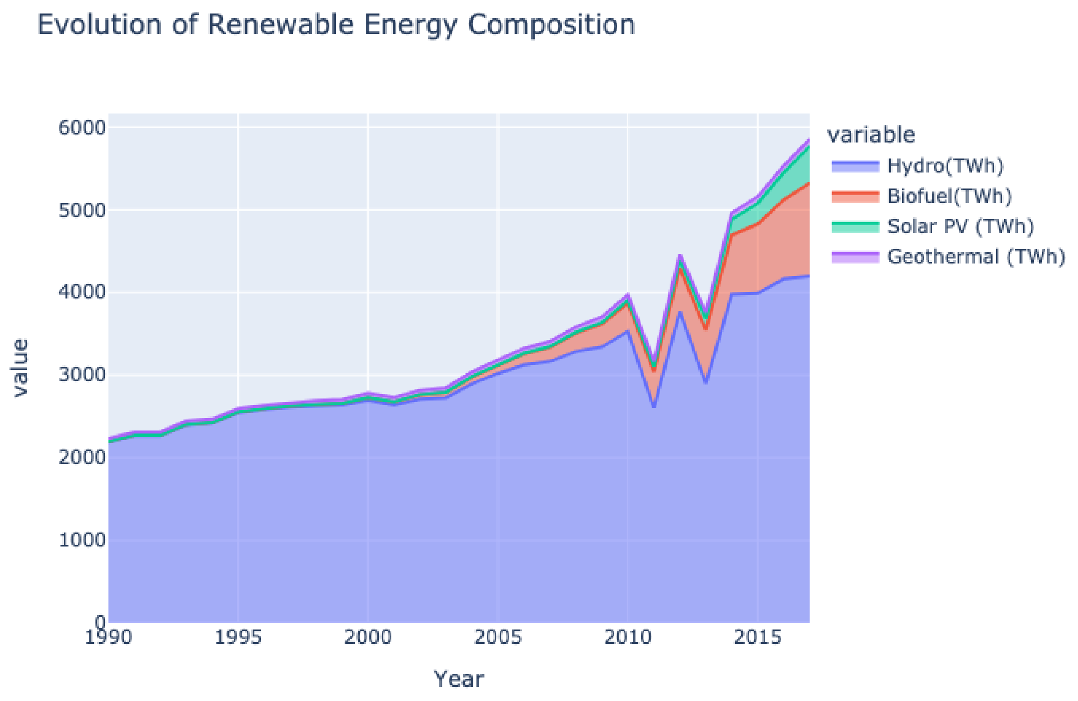
- Short-term (1-3 months):
    - Attention mechanism integration
    - Transfer learning implementation
    - Hybrid architecture development
- Medium-term (6-12 months):
    - Distributed training system
    - Cross-region adaptation
    - Automated deployment
- Long-term (12-24 months):
    - Grid management integration
    - Causal inference methods
    - Continuous learning system



Conclusion

Research Impact

- Key Contributions:
  - Novel ensemble architecture for renewable energy prediction
  - Advanced feature engineering techniques
  - Efficient computational framework
- Practical Applications:
  - Improved prediction accuracy ($R^2 = 0.6964$)
  - Reduced computational overhead
  - Enhanced scalability



[GitHub Repository]

Thank you!