

Solar Panel Output Prediction Using ML With Weather Data

Capstone Project Phase A - 61998

Team Members: Yovel Jirad and Shay Pinsky

Supervisors: Dr. Dan Lemberg and Mrs. Elena Kramer

April 2025

The Challenge of Solar Energy Integration



Growth & Variability

Solar energy experiencing exponential growth globally, but faces inherent variability due to weather conditions.



Grid Management

Grid operators struggle to:

- Balance supply and demand in real-time.
- Schedule maintenance.
- Choose efficient locations for solar farms



Forecasting Limitations

Traditional forecasting methods have significant limitations:

- Poor handling of non-linear relationships
- Computational inefficiency
- Limited multi-horizon capabilities



Critical Need

Reliable forecasting for optimal grid integration



Problem Statement & Our Approach

Problem

- Multi-horizon prediction challenges
- Inadequate weather parameter integration
- Lack of real-time processing capabilities
- Geographic and temporal specificity requirements

Our Solution

- Dual-architecture machine learning system
- GRU networks for short-term forecasting (0-24 hours)
- Autoformer for long-term forecasting (2-4 days)
- Real-time weather data integration from IMS API

Project Objectives

Primary Goals

- Achieve $\leq 10\%$ error margin for day-ahead forecasts
- Provide reliable predictions up to 4 days ahead
- Create unified web-based forecasting platform
- Support both operational and strategic energy planning

Target Metrics

- MAPE $\leq 10\%$ for day-ahead predictions
- $R^2 \geq 90\%$ to match literature standards
- Response time ≤ 30 seconds per request
- Real-time data querying within 30 minutes

Literature Review & Market Analysis

Current Limitations:

- Single-architecture solutions dominate the market
- Limited multi-horizon forecasting capabilities
- Generic models fail to capture location-specific patterns

Research Foundation:

- Jebli et al. (2021): Pearson correlation for parameter selection
- Casolaro et al. (2023): Deep learning architectures comparison
- Established photovoltaic output equation validation



Data Strategy & Key Decisions

Weather Data Source

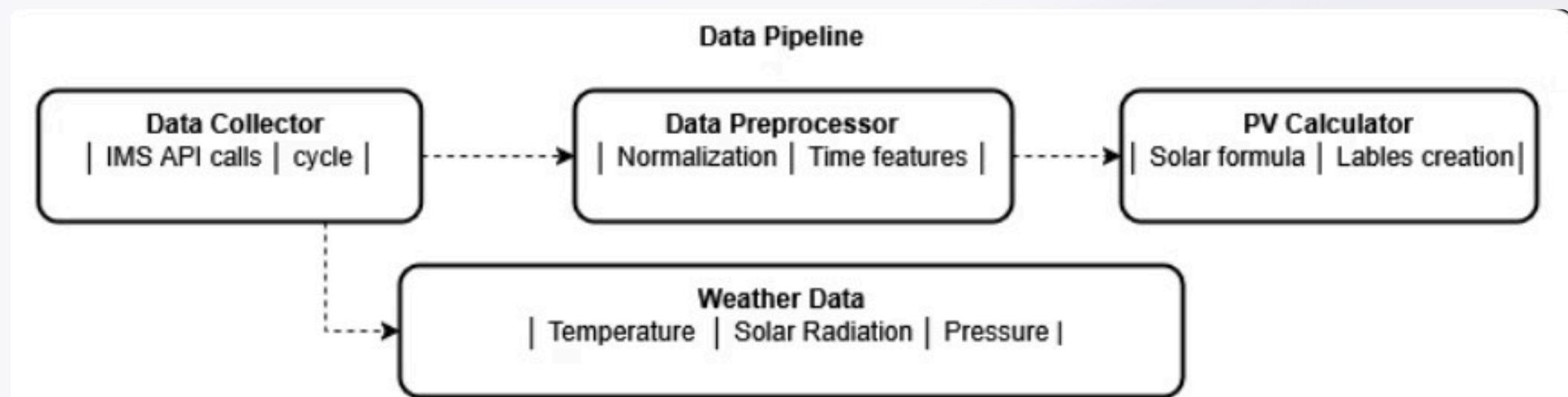
- Israel Meteorological Service (IMS) API
- Parameters: Temperature, solar radiation, humidity, pressure
- Real-time updates every 30 minutes

Solar Data Challenge

- Direct solar farm data unavailable (proprietary)
- **Solution:** Theoretical photovoltaic calculation approach
- Equation: $P_{out,pv} = C_R,PV \times (G_T/G_{T,STC}) \times [1 + \alpha_p(T_C - T_{C,STC})]$

Feature Selection

- Pearson correlation analysis for parameter optimization



Development Challenges & Constraints

Technical Challenges

- Dual-architecture complexity
- Real-time data processing requirements
- Model optimization for accuracy targets
- System integration across multiple components

External Constraints

- 5-month development timeline (Aug 2024 - Jan 2025)
- Military reserve duty disruptions during wartime
- Work-study balance challenges
- Limited computational resources

Risk Mitigation

- Agile development approach
- Comprehensive documentation strategy
- Cloud computing utilization

Technical Approach & Tools

Machine Learning Framework

- TensorFlow/Keras for deep learning implementation
- Python ecosystem (Pandas, NumPy, Scikit-learn)
- Grid search hyperparameter optimization

Development Tools

- Git & GitHub for version control
- Google Colab for model training
- Flask for API development
- React.js for web interface

Evaluation Strategy

- Time series cross-validation
- Multiple metrics: MAE, RMSE, MAPE, R²
- Comparison with baseline methods

Short-Term Forecasting: GRU Architecture



GRU Network Design

- Two stacked GRU layers (64, 32 hidden units)
- Dropout regularization (20%)
- Recursive prediction methodology



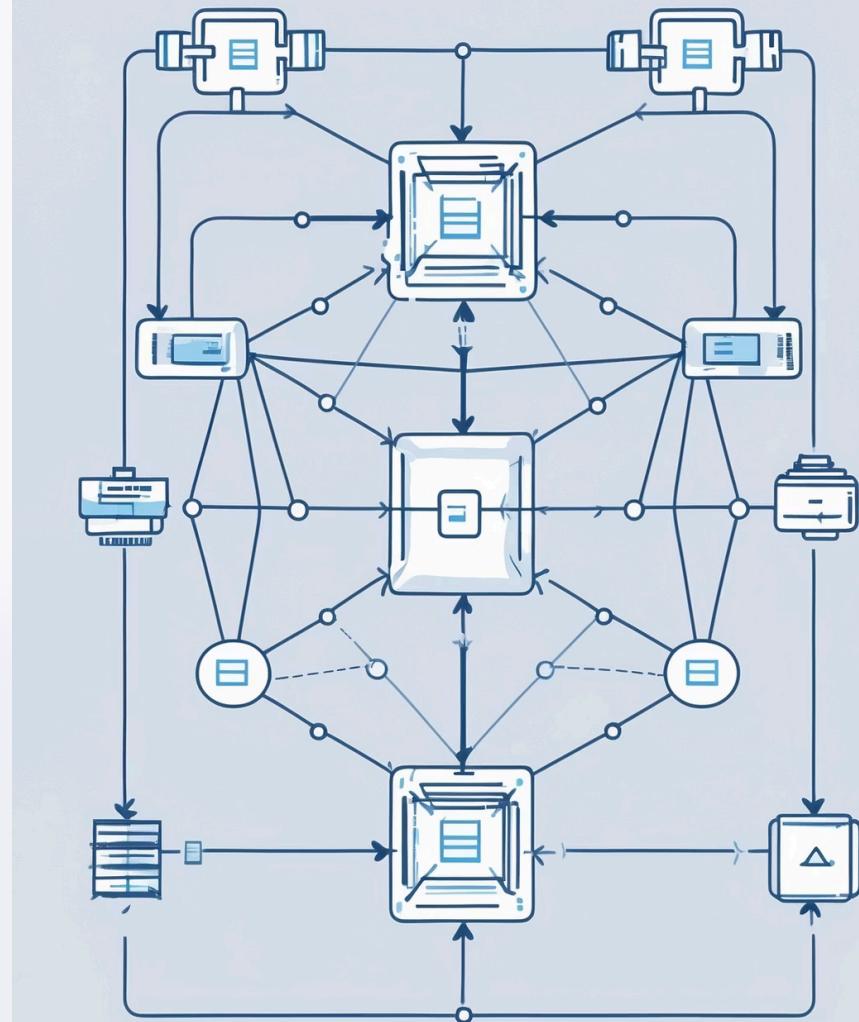
Key Operations

- Reset gate: Controls information retention
- Update gate: Balances new vs. previous information
- Candidate state: Generates memory proposals
- Final state: Combines via gating mechanism

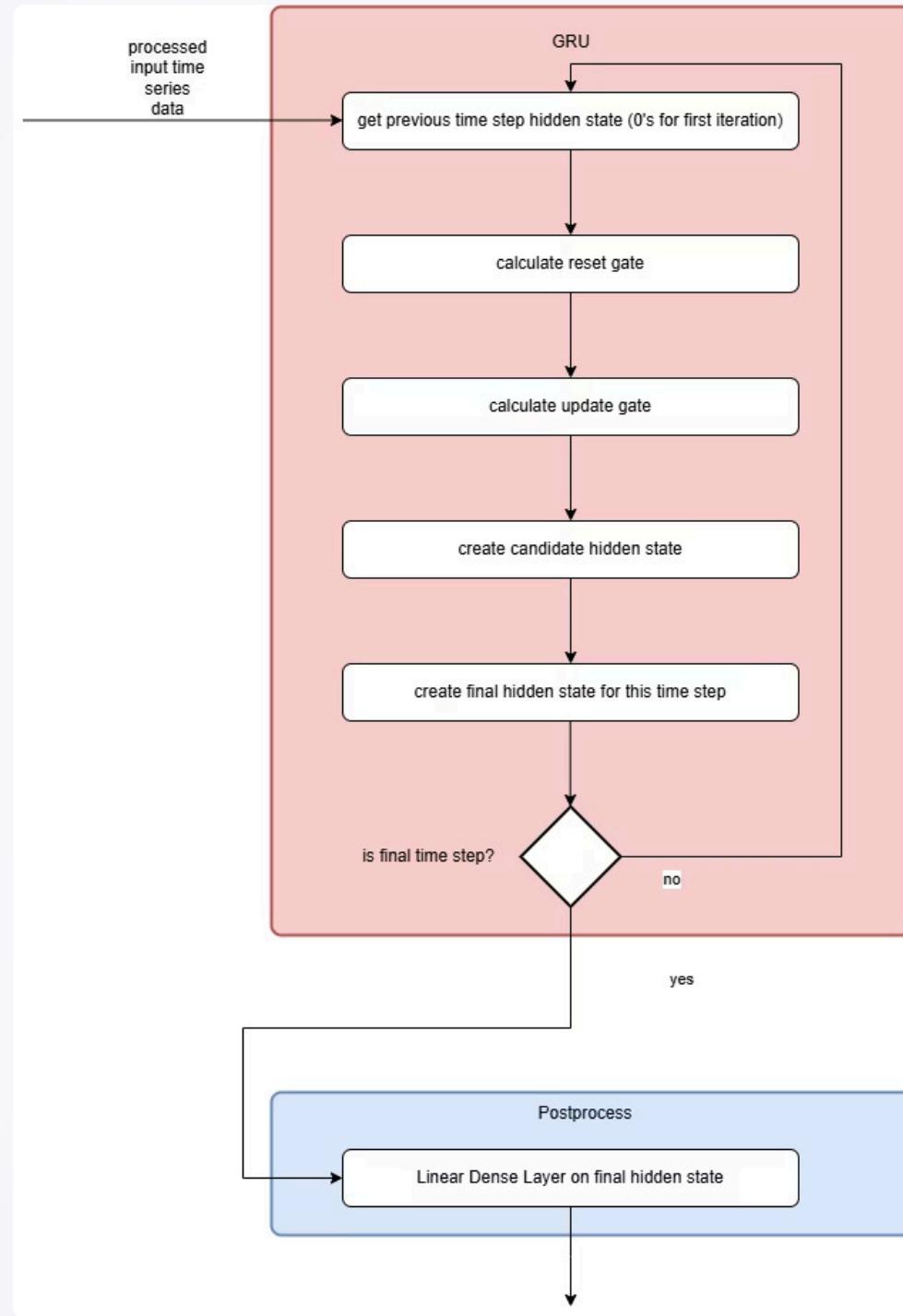


Target

Hourly predictions for next 24 hours



GRU Architecture Diagram



Long-Term Forecasting: Autoformer Architecture



Autoformer Design

- 4 encoder layers, 2 decoder layers
- Autocorrelation mechanism replaces attention
- Series decomposition for trend/seasonal separation



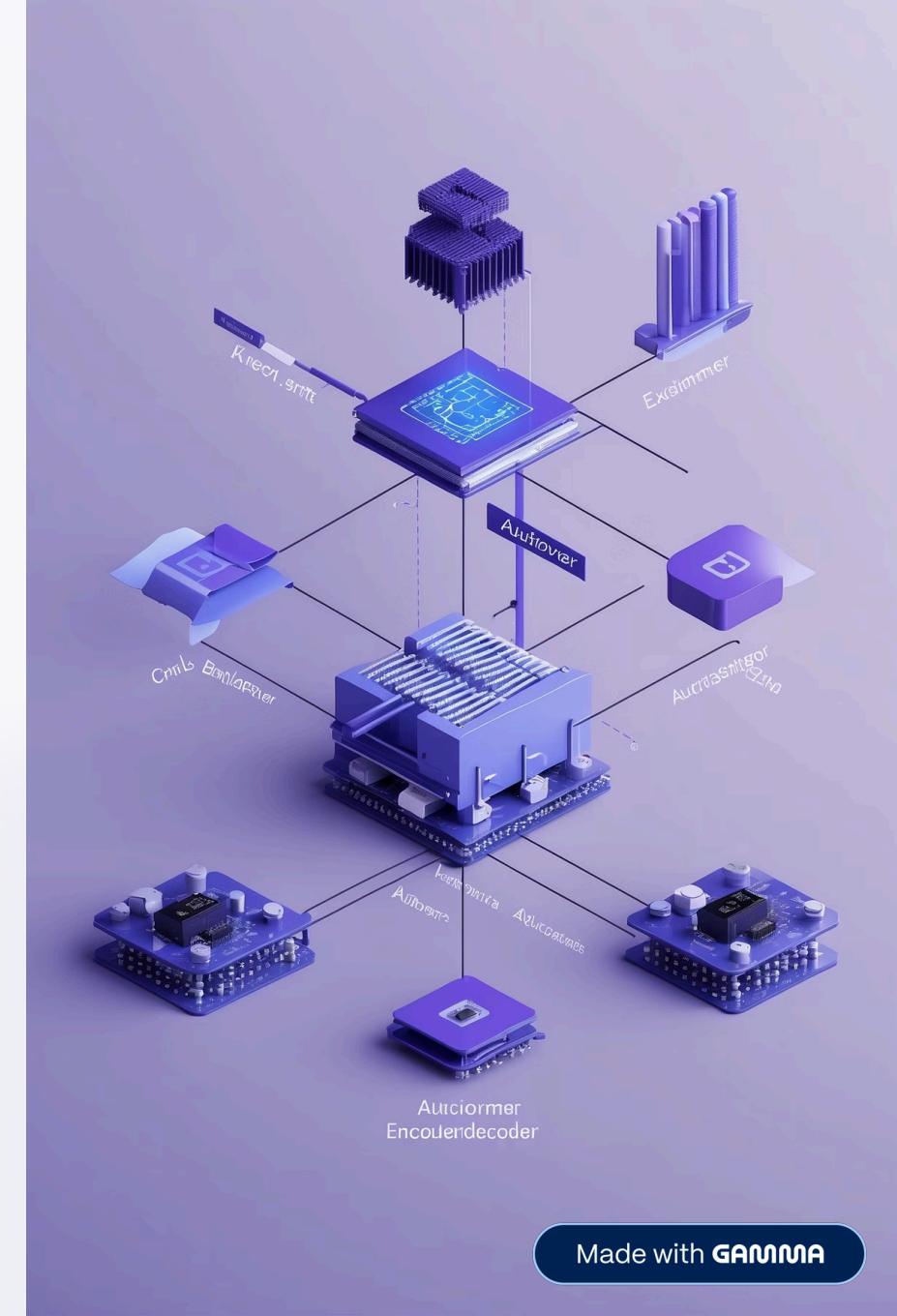
Key Mechanisms

- Auto-correlation: Identifies recurring patterns
- Moving average pooling: Extracts trend components
- Cross-attention: Encoder-decoder information exchange

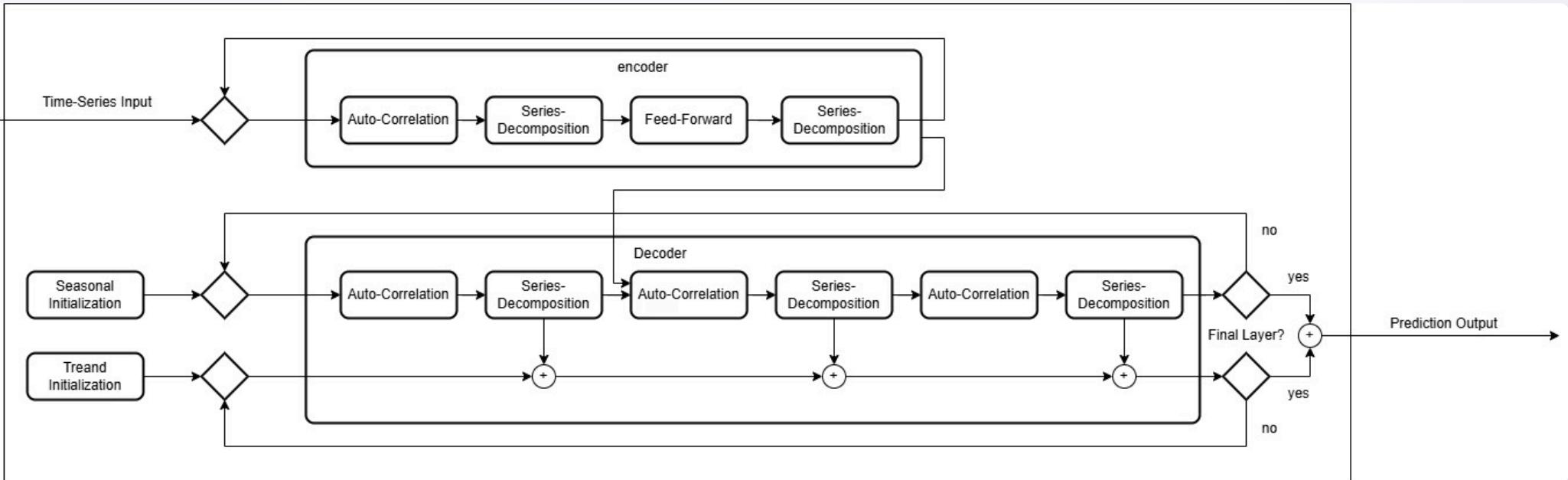


Target

Daily predictions for 2-4 days ahead



Autoformer Architecture Diagram



Complete System Architecture

System Components:



Data Acquisition Layer

IMS API integration for weather data collection



Preprocessing Module

Normalization, feature selection



Dual-Model Prediction Engine

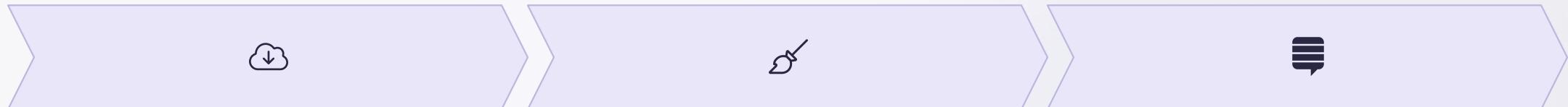
GRU and Autoformer architectures



Web Interface

RESTful APIs for user interaction

Processing Flow:



1. Data Collection

Real-time weather data collection

2. Preprocessing

Data cleaning and preprocessing

3. Model Selection

Based on forecast horizon



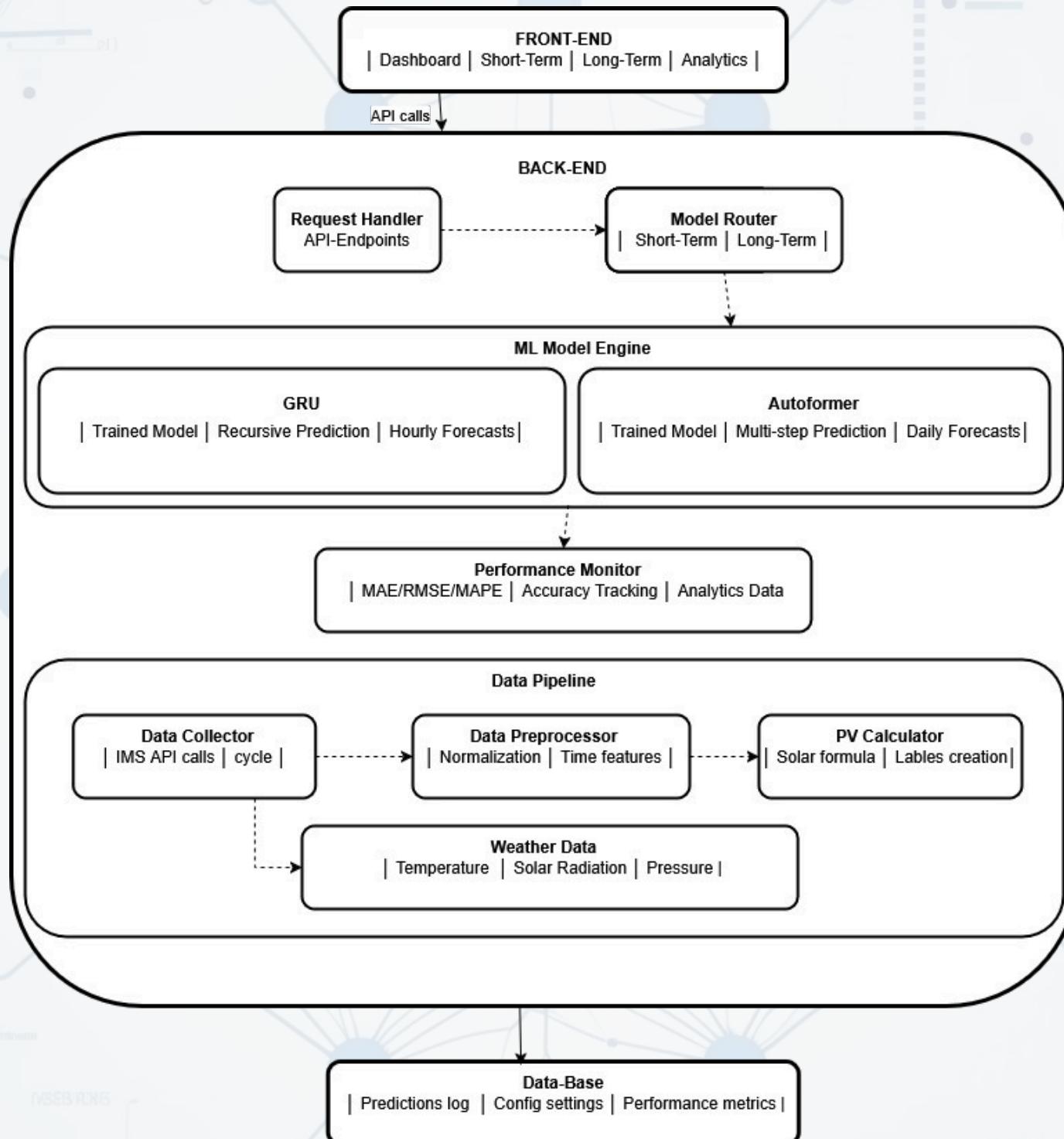
4. Prediction

Generation and delivery

5. Monitoring & Logging

Performance monitoring and updates

System architecture overview diagram



Web Application Interface

Our solution provides a comprehensive interface with four main pages designed for both technical and non-technical users:



Dashboard

Current predictions and quick navigation to all system features



Short-Term Forecast

Hourly predictions with confidence intervals for next-day planning



Long-Term Forecast

Multi-day predictions with seasonal analysis for extended planning



Performance Analytics

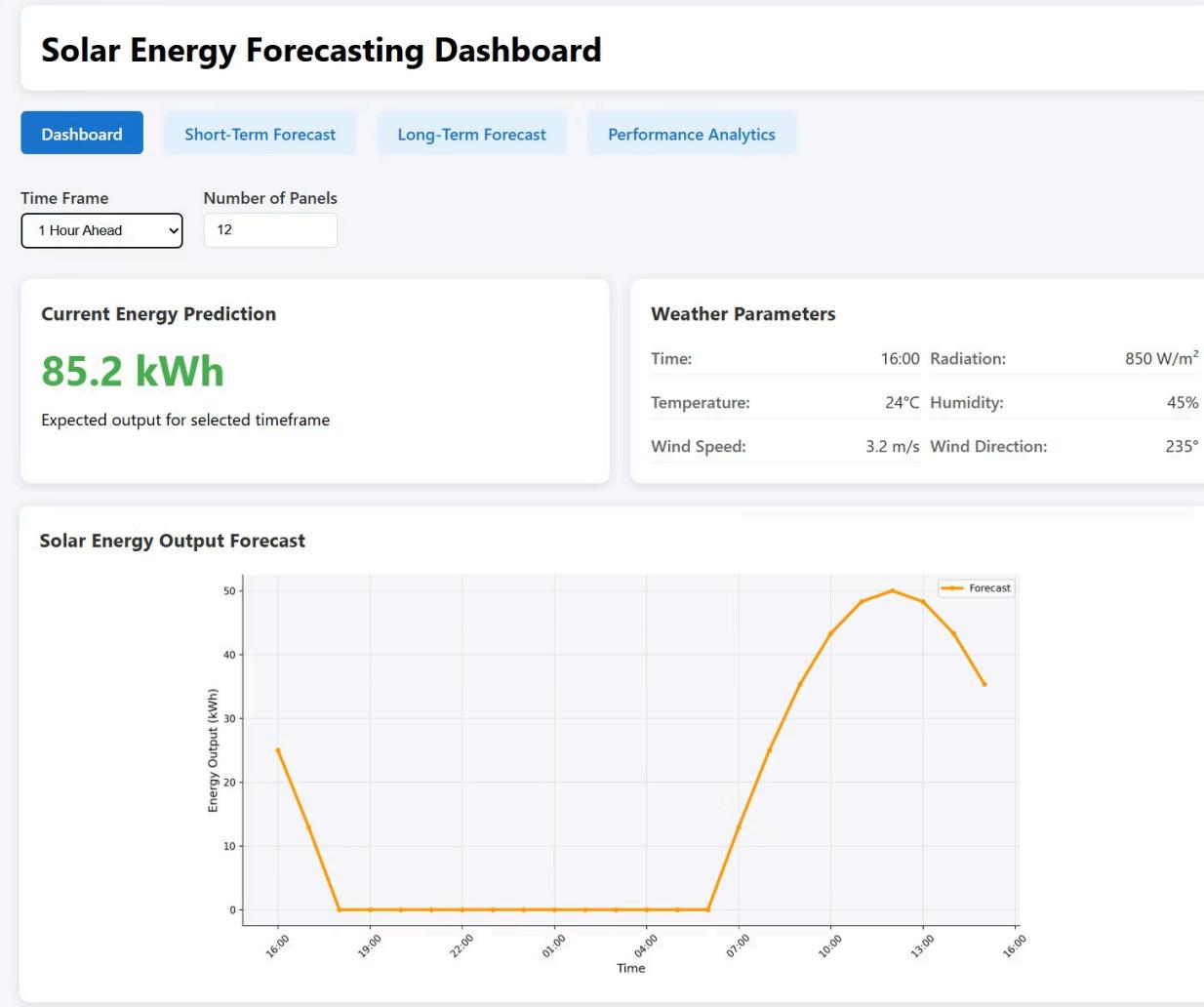
Accuracy tracking and model comparison for system validation

Key Features

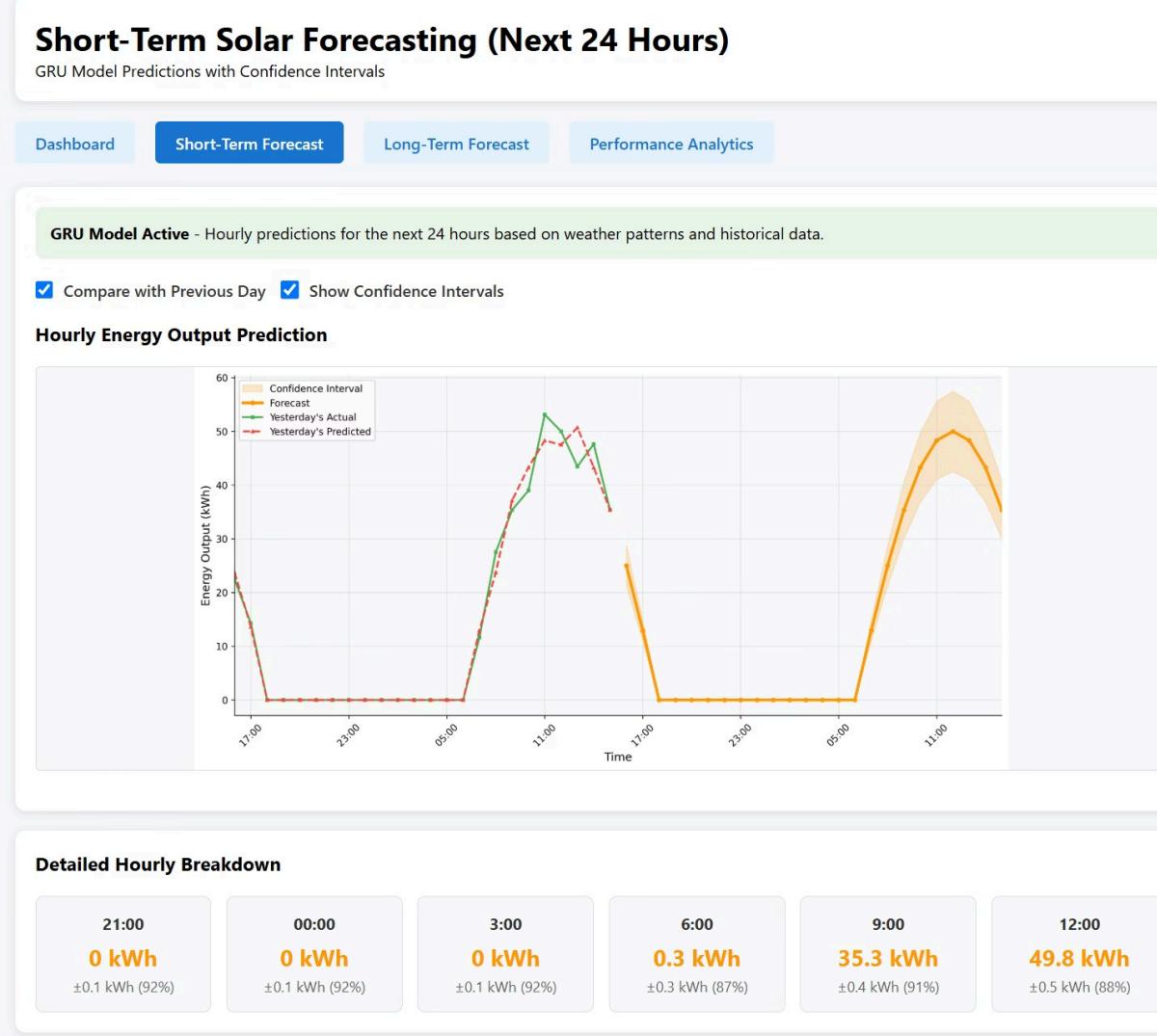
Key Features

- Interactive visualizations
- Real-time updates
- Mobile-responsive design
- Technical and non-technical user support

Dashboard



Short-Term Forecast



Long-Term Forecast

Long-Term Solar Forecasting (2-4 Days)

Autoformer Model Predictions with Seasonal Analysis

Dashboard

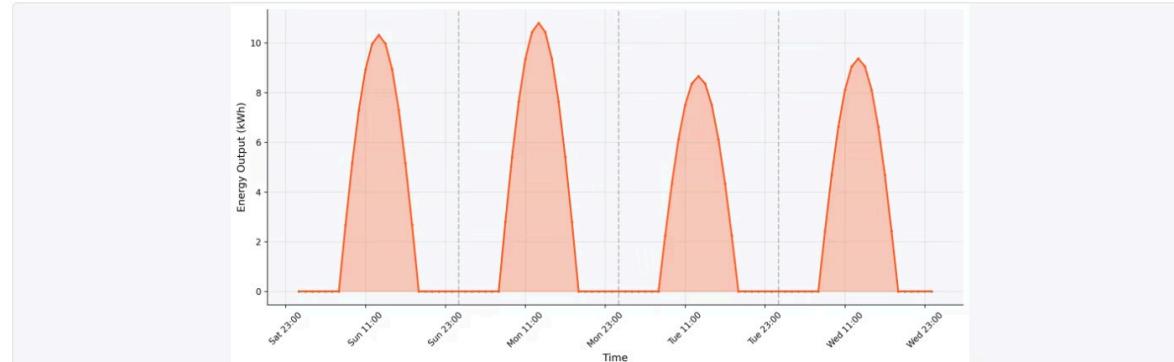
Short-Term Forecast

Long-Term Forecast

Performance Analytics

Autoformer Model Active - Multi-day predictions incorporating seasonal patterns and weather correlations.

Multi-Day Energy Forecast



Tomorrow

78.4 kWh

Peak: 12:30 PM
Confidence: 84%

Day 2

82.1 kWh

Peak: 1:00 PM
Confidence: 79%

Day 3

65.8 kWh

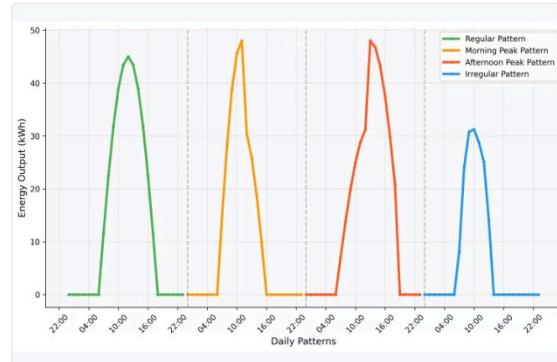
Peak: 11:45 AM
Confidence: 72%

Day 4

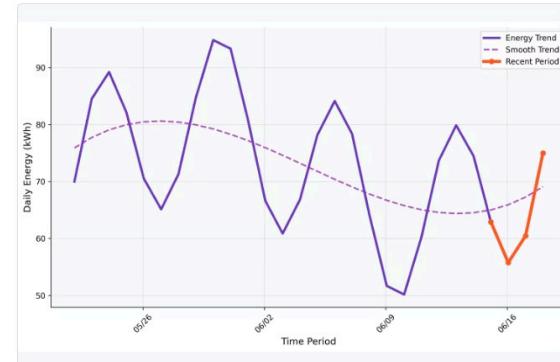
71.2 kWh

Peak: 12:15 PM
Confidence: 68%

Seasonal Data



Trend Data



Performance Analytics

Performance Analytics & Model Validation

Historical accuracy metrics and model performance comparison

Dashboard

Short-Term Forecast

Long-Term Forecast

Performance Analytics

Current Model Accuracy Metrics

MEAN ABSOLUTE ERROR (MAE)

2.34 kWh

Excellent

ROOT MEAN SQUARE ERROR (RMSE)

3.78 kWh

Good

MEAN ABSOLUTE PERCENTAGE ERROR (MAPE)

8.2%

Good

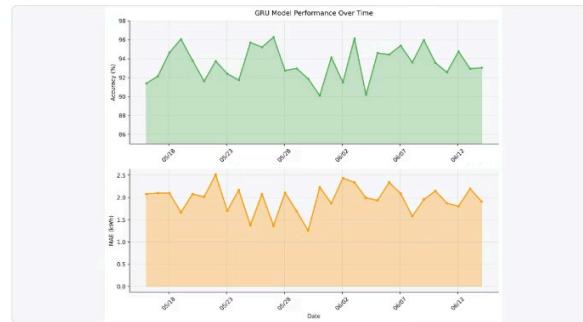
OVERALL ACCURACY

91.8%

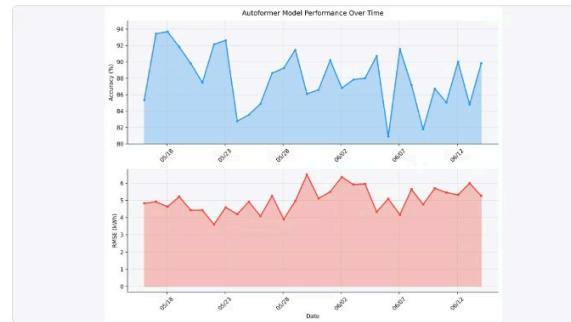
Excellent

Model Performance Comparison

GRU Model (Short-term)



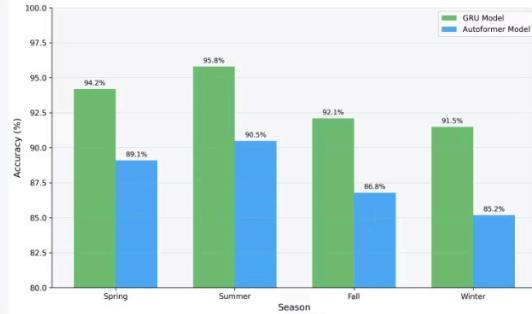
Autoformer Model (Long-term)



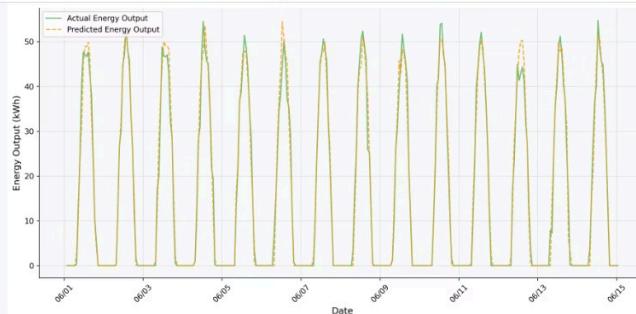
Model	Time Horizon	MAE (kWh)	RMSE (kWh)	MAPE (%)	Accuracy (%)
GRU	1-24 hours	1.89	2.76	6.4	93.6
Autoformer	2-4 days	3.12	4.85	11.8	88.2

Performance Analytics

Seasonal Accuracy Analysis



Prediction vs Actual Comparison



Validation Strategy & Expected Outcomes

Our comprehensive approach to validating the solar prediction model:



Testing Methodology

- Walk-forward validation (18 months training, 3 months validation)
- Baseline comparisons (persistence, linear regression, moving averages)
- Seasonal and weather-condition stratification
- Multi-horizon performance assessment



Expected Results

- MAPE $\leq 10\%$ for day-ahead forecasts
- Superior performance vs. traditional methods
- Consistent accuracy across seasons
- Real-time processing capability demonstration



Success Metrics

- $R^2 \geq 90\%$ (matching literature benchmarks)
- 15% RMSE improvement over persistence model



Development Roadmap

A structured 6-phase approach to implementation:





Anticipated Challenges



Key Challenges

- Achieving 10% MAPE accuracy target
- Military service disruptions
- Model complexity and computational requirements
- System integration under time constraints



Mitigation Strategies

- Automated hyperparameter optimization
- Comprehensive documentation and modular design
- Cloud computing resources
- Incremental integration approach
- Working in agile methodology

Summary & Future Outlook

Project Summary

- Dual-architecture ML system for solar energy forecasting
- Integration of GRU (short-term) and Autoformer (long-term)
- Real-time web platform with comprehensive analytics
- Target: $\leq 10\%$ error margin for day-ahead predictions

Expected Impact

- Enhanced grid integration capabilities
- Improved renewable energy planning
- Contribution to climate change mitigation
- Academic research advancement

Thank You

We appreciate your attention and support for our solar energy forecasting project.

25

