BRAUDE
College of Engineering, Karmiel

Solar Panel Output Prediction Using ML With Weather Data

Capstone Project Phase A - 61998

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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.

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 ≤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 ≤ 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
- Insufficient real-world validation with operational data
- 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

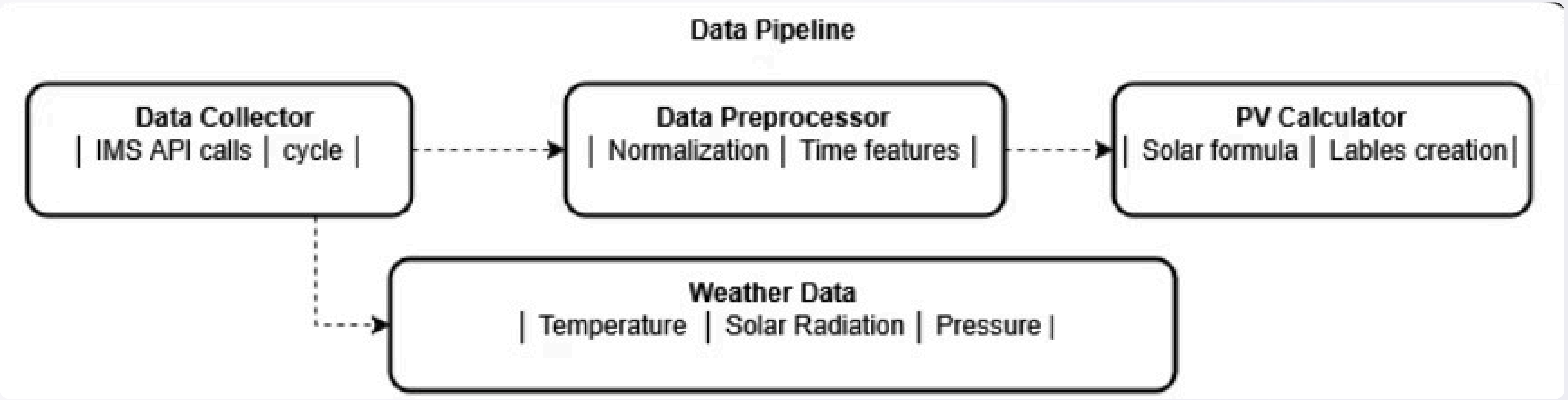
- Israel Meteorological Service (IMS) API
- Parameters: Temperature, solar radiation, humidity, pressure
- Real-time updates every 30 minutes

Solar Data Challenge

- Direct solar farm data unavailable (proprietary)
- **Solution:** Theoretical photovoltaic calculation approach
- Equation: P_out,pv = C_R,PV × (G_T/G_T,STC) × [1 + α_p(T_C - T_C,STC)]

Feature Selection

- Pearson correlation analysis for parameter optimization



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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, R^2
- Comparison with baseline methods

Short-Term Forecasting: GRU Architecture

GRU Network Design

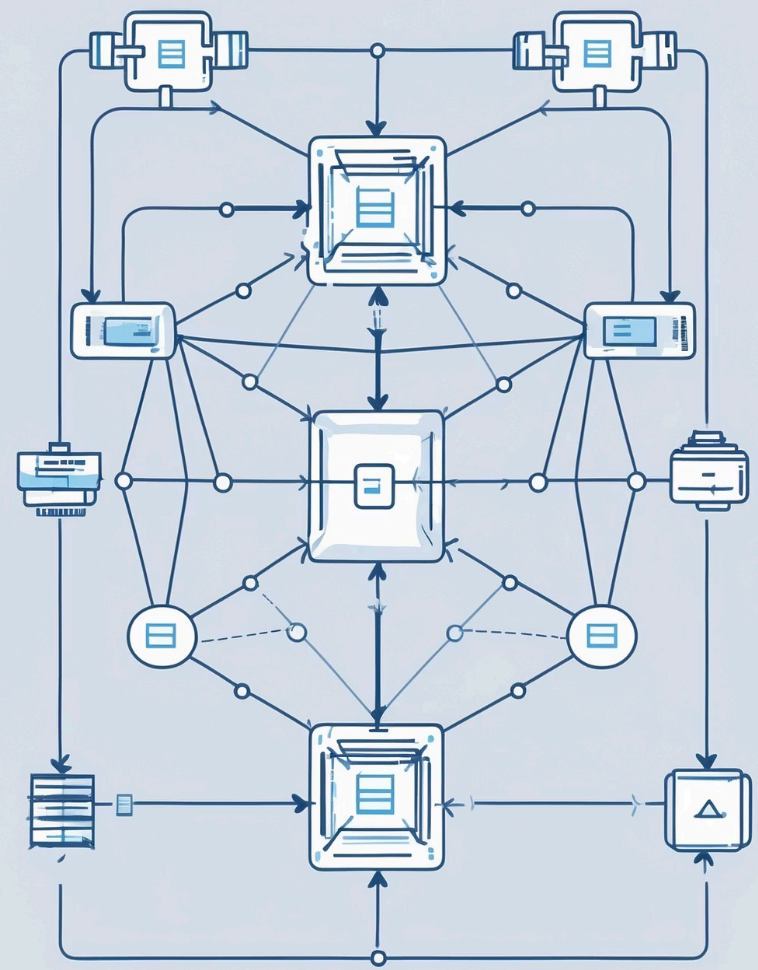
- Two stacked GRU layers (64, 32 hidden units)
- Dropout regularization (20%)
- Recursive prediction methodology

Key Operations

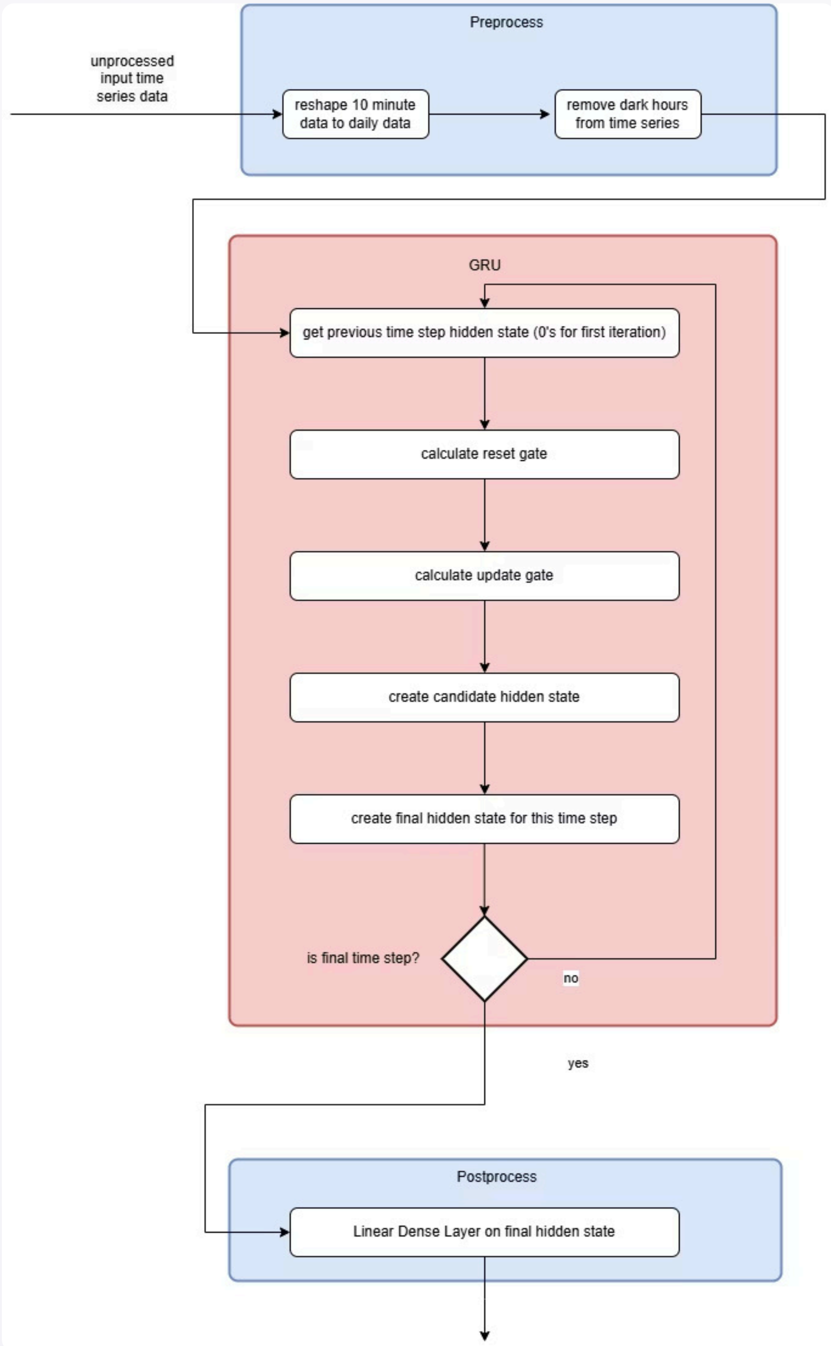
- Reset gate: Controls information retention
- Update gate: Balances new vs. previous information
- Candidate state: Generates memory proposals
- Final state: Combines via gating mechanism

Target

Hourly predictions for next 24 hours



GRU Architecture Diagram



Long-Term Forecasting: Autoformer Architecture

Autoformer Design

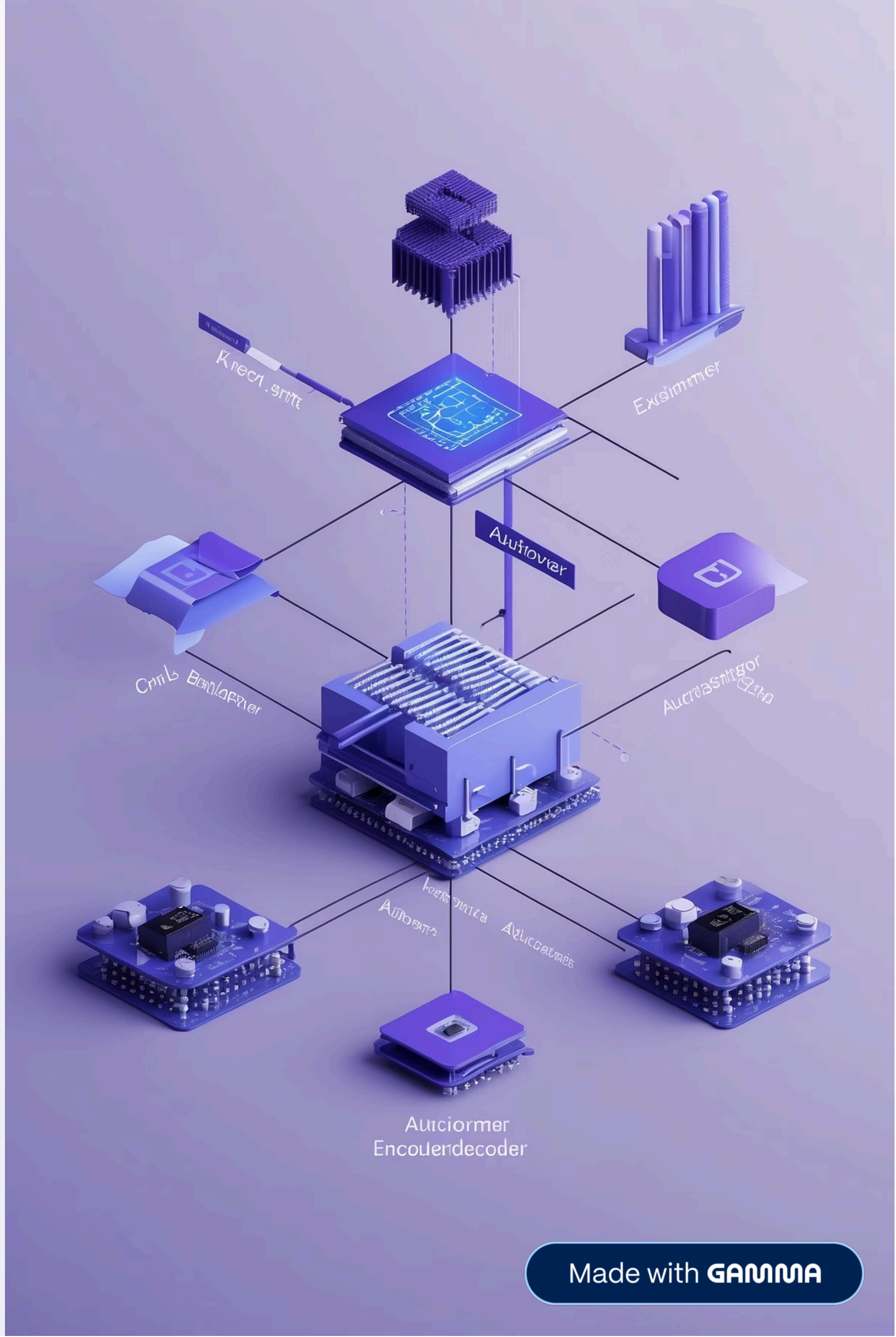
- 4 encoder layers, 2 decoder layers
- Autocorrelation mechanism replaces attention
- Series decomposition for trend/seasonal separation

Key Mechanisms

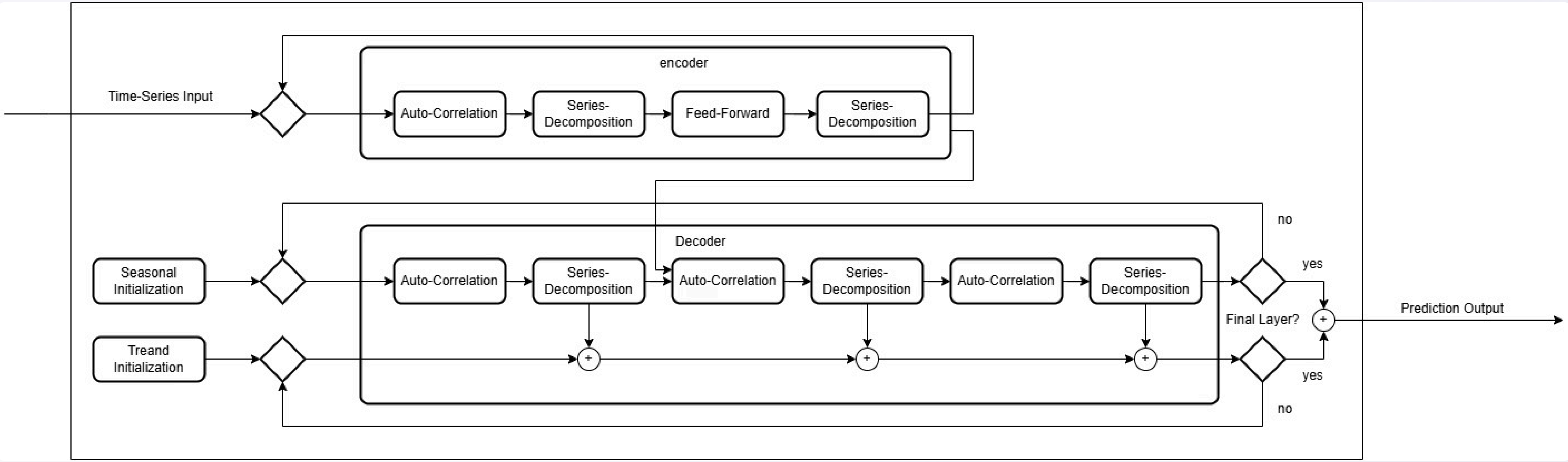
- Auto-correlation: Identifies recurring patterns
- Moving average pooling: Extracts trend components
- Cross-attention: Encoder-decoder information exchange

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

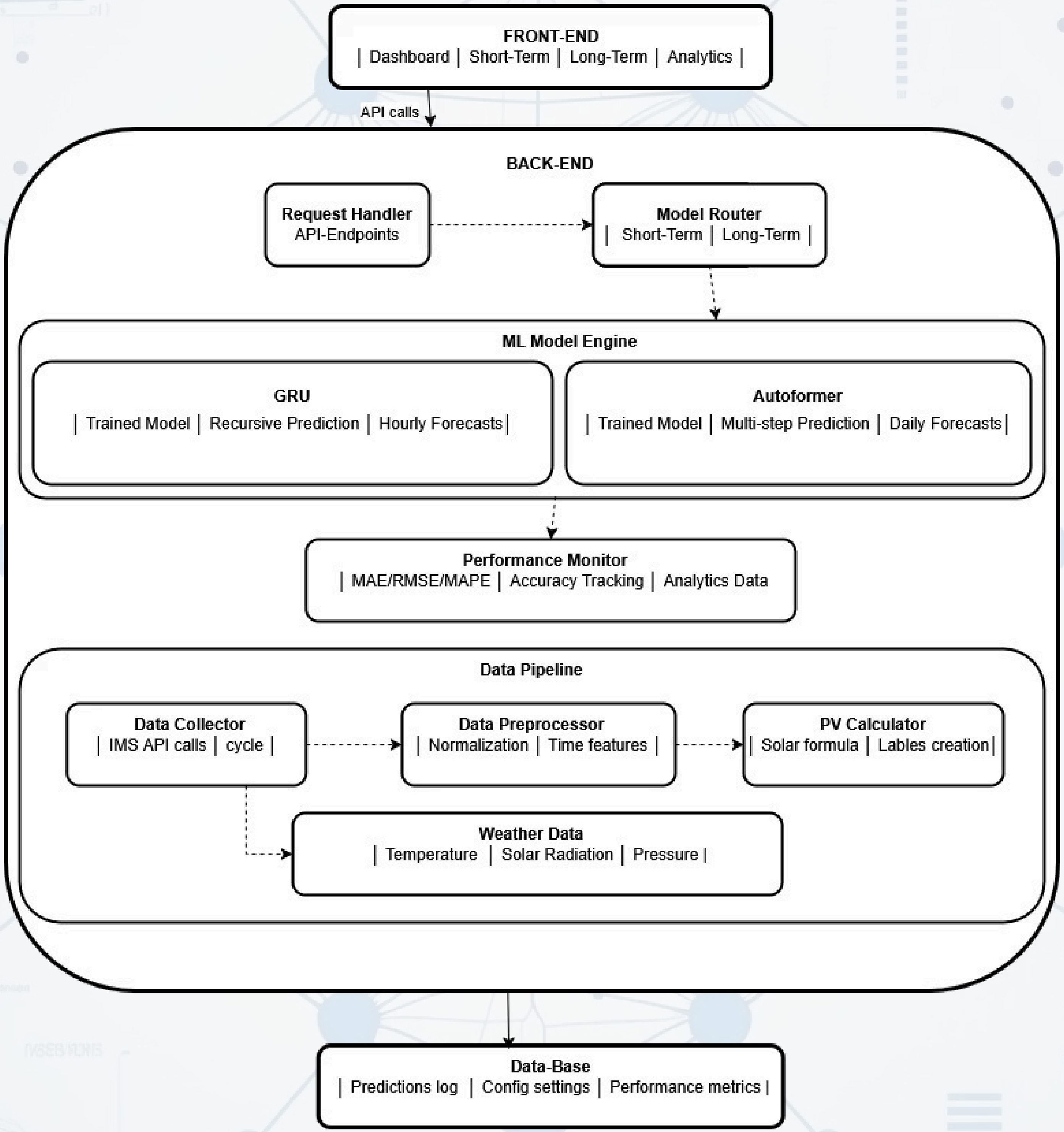
4. Prediction

Generation and delivery

5. Monitoring

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

Solar Energy Forecasting Dashboard

Dashboard | Short-Term Forecast | Long-Term Forecast | Performance Analytics

Time Frame: 1 Hour Ahead

Number of Panels: 12

Current Energy Prediction

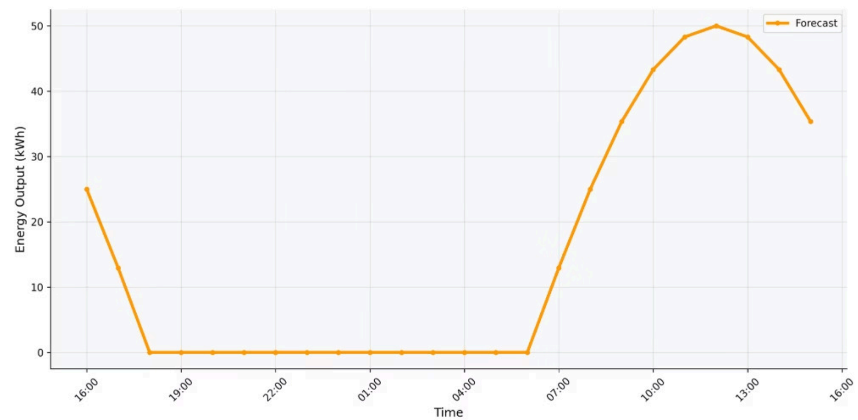
85.2 kWh

Expected output for selected timeframe

Weather Parameters

Time:	16:00	Radiation:	850 W/m^2
Temperature:	24°C	Humidity:	45%
Wind Speed:	3.2 m/s	Wind Direction:	235°

Solar Energy Output Forecast



Short-Term Forecast

Short-Term Solar Forecasting (Next 24 Hours)

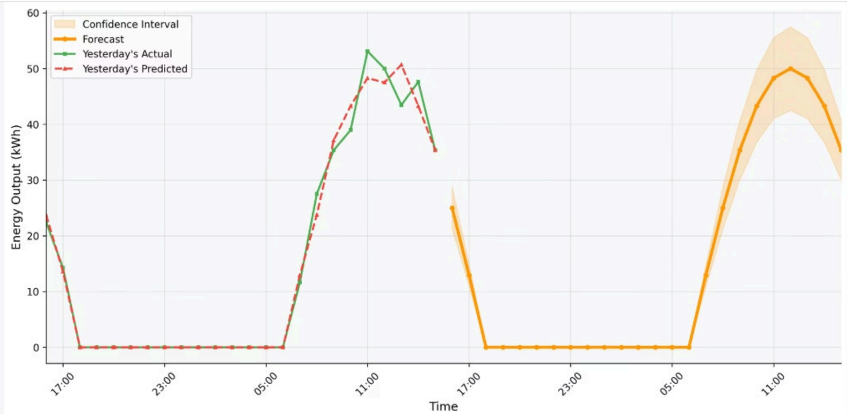
GRU Model Predictions with Confidence Intervals

Dashboard | Short-Term Forecast | Long-Term Forecast | Performance Analytics

GRU Model Active - Hourly predictions for the next 24 hours based on weather patterns and historical data.

☑ Compare with Previous Day ☑ Show Confidence Intervals

Hourly Energy Output Prediction



Detailed Hourly Breakdown

21:00	00:00	3:00	6:00	9:00	12:00
0 kWh	0 kWh	0 kWh	0.3 kWh	35.3 kWh	49.8 kWh
±0.1 kWh (92%)	±0.1 kWh (92%)	±0.1 kWh (92%)	±0.3 kWh (87%)	±0.4 kWh (91%)	±0.5 kWh (88%)

Long-Term Forecast

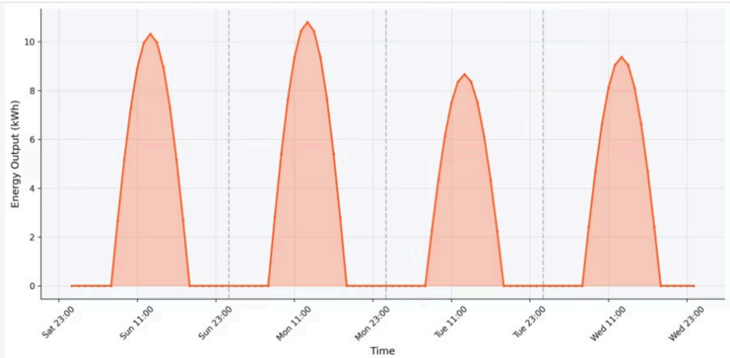
Long-Term Solar Forecasting (2-4 Days)

Autoformer Model Predictions with Seasonal Analysis

Dashboard | Short-Term Forecast | Long-Term Forecast | Performance Analytics

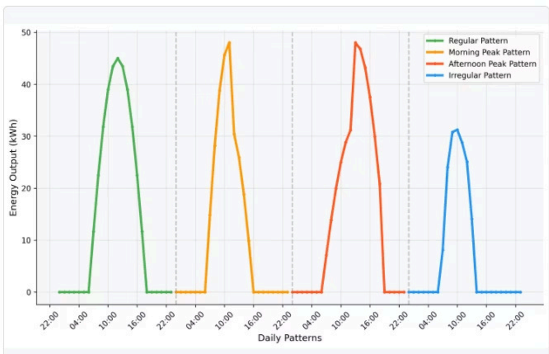
Autoformer Model Active - Multi-day predictions incorporating seasonal patterns and weather correlations.

Multi-Day Energy Forecast

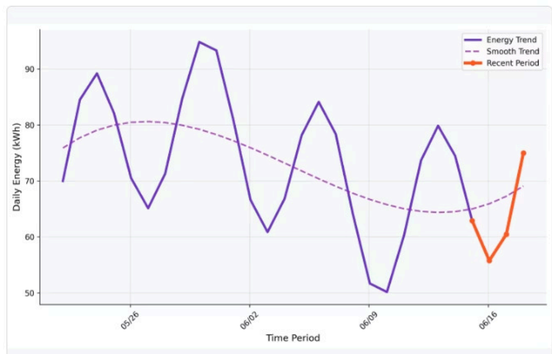


Tomorrow	Day 2	Day 3	Day 4
78.4 kWh	**82.1 kWh**	**65.8 kWh**	**71.2 kWh**
Peak: 12:30 PM	Peak: 1:00 PM	Peak: 11:45 AM	Peak: 12:15 PM
Confidence: 84%	Confidence: 79%	Confidence: 72%	Confidence: 68%

Seasonal Data



Trend Data



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Performance Analytics

Performance Analytics & Model Validation

Historical accuracy metrics and model performance comparison

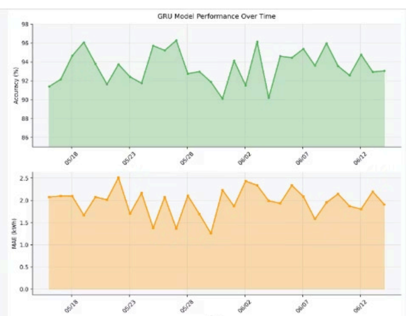
Dashboard | Short-Term Forecast | Long-Term Forecast | **Performance Analytics**

Current Model Accuracy Metrics

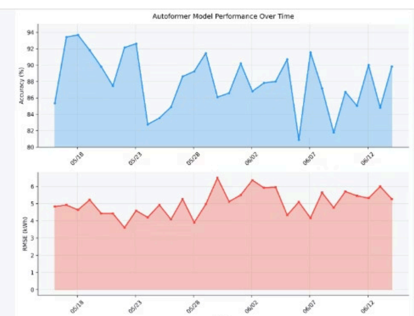
MEAN ABSOLUTE ERROR (MAE)	ROOT MEAN SQUARE ERROR (RMSE)	MEAN ABSOLUTE PERCENTAGE ERROR (MAPE)	OVERALL ACCURACY
2.34 kWh	**3.78 kWh**	**8.2%**	**91.8%**
Excellent	Good	Good	Excellent

Model Performance Comparison

GRU Model (Short-term)



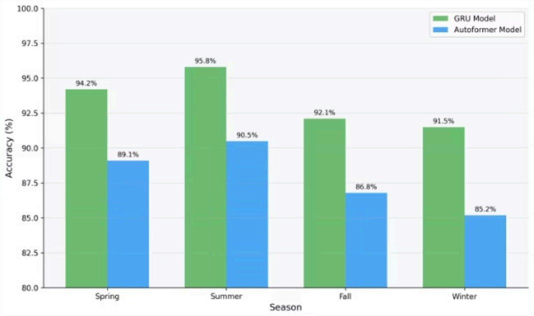
Autoformer Model (Long-term)



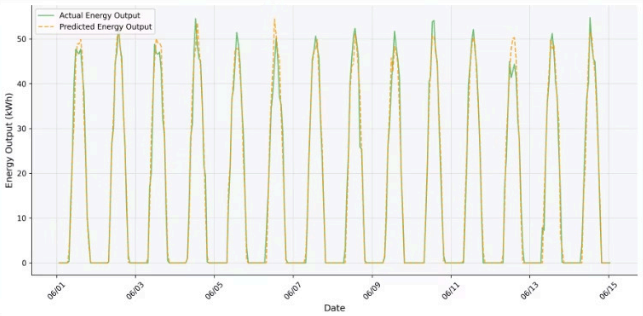
Model	Time Horizon	MAE (kWh)	RMSE (kWh)	MAPE (%)	Accuracy (%)
GRU	1-24 hours	1.89	2.76	6.4	93.6
Autoformer	2-4 days	3.12	4.85	11.8	88.2

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 ≤ 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:

1 Phase 1: Data Processing

- API Integration Enhancement with IMS
- Data Quality Assurance & Preprocessing Framework
- Photovoltaic Calculation Implementation

2 Phase 2: Model Development and Training

- GRU Model Implementation (64-32 hidden units, dropout 0.2)
- Autoformer Model Implementation (4 encoder, 2 decoder layers)
- Hyperparameter Optimization & Training Pipeline

3 Phase 3: Model Integration and Evaluation

- Dual-Model Integration & Pipeline Coordination
- Comprehensive Evaluation Framework (MAE, RMSE, MAPE, R^2)
- Baseline Comparisons & Cross-Validation

4 Phase 4: Web Application Development

- Backend Development (Flask/FastAPI, Database Integration)
- Frontend Development (React.js, Interactive Dashboard)
- RESTful API Implementation

5 Phase 5: Testing and Validation

- End-to-End System Integration Testing
- Load Testing & Accuracy Validation
- Technical & User Documentation

6 Phase 6: Final Validation and Project Completion

- Live Testing & Performance Validation
- Comparative Analysis & Seasonal Assessment
- Final Report & System Demonstration

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: ≤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.

> Harnessing the power of machine learning to predict the future of clean energy.

We welcome any questions or feedback on our proposed solution.