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.
- 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 ≤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
- 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

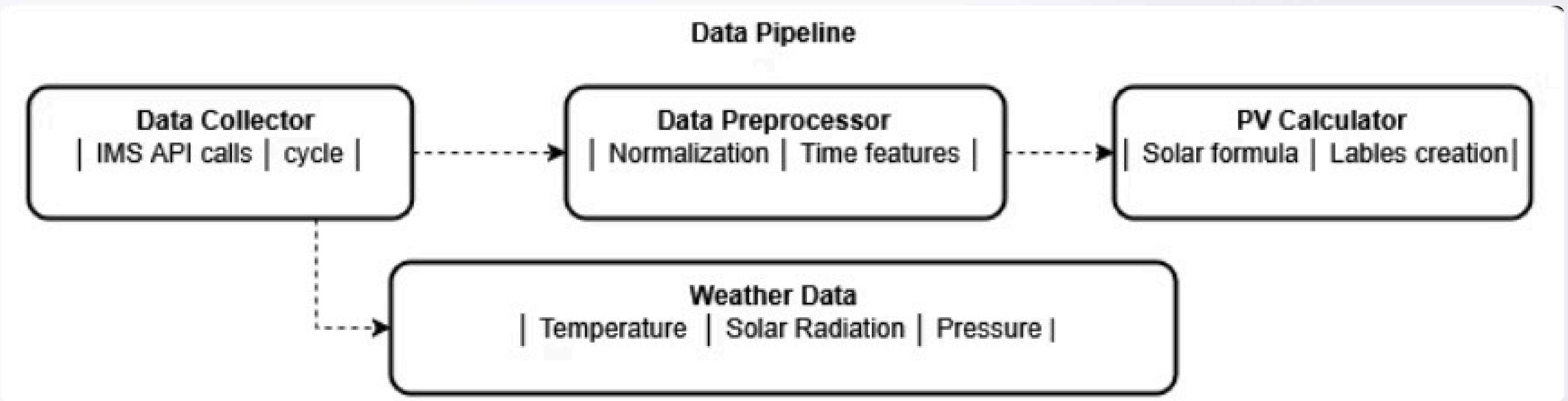
- Israel Meteorological Service (IMS) API
- Parameters: Temperature, solar radiation, humidity, pressure
- Real-time updates every 30 minutes

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, R^2
- Comparison with baseline methods

Short-Term Forecasting: GRU Architecture

GRU Network Design

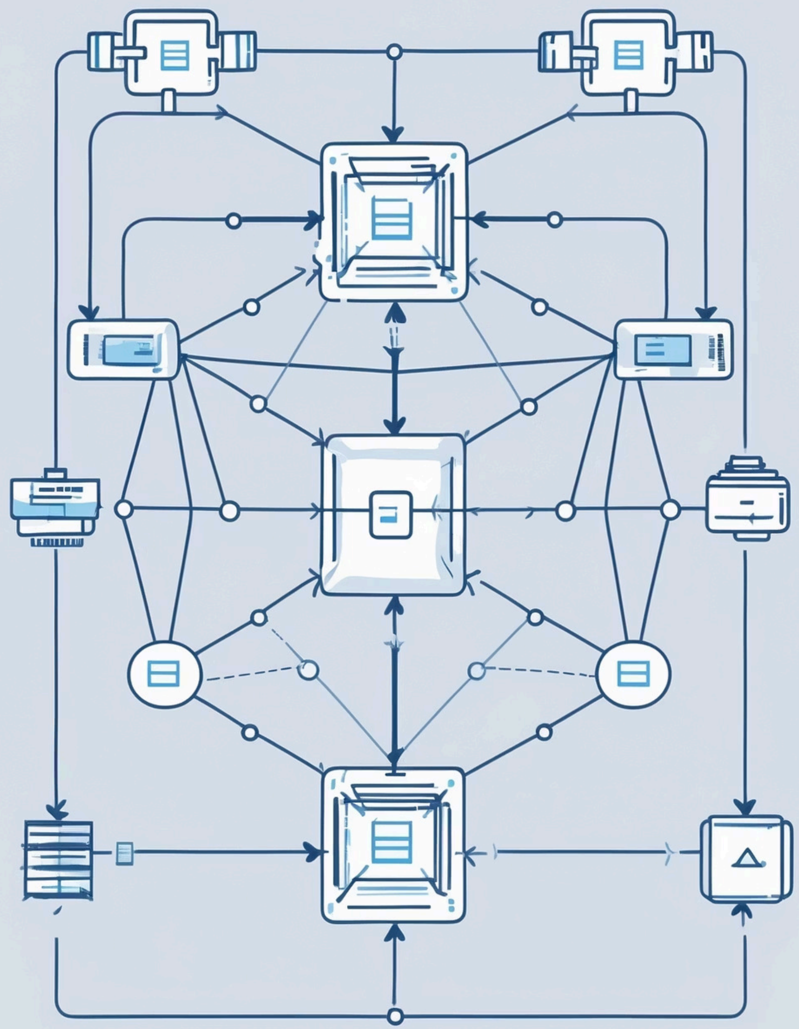
- Two stacked GRU layers (64, 32 hidden units)
- Dropout regularization (20%)
- Recursive prediction methodology

Key Operations

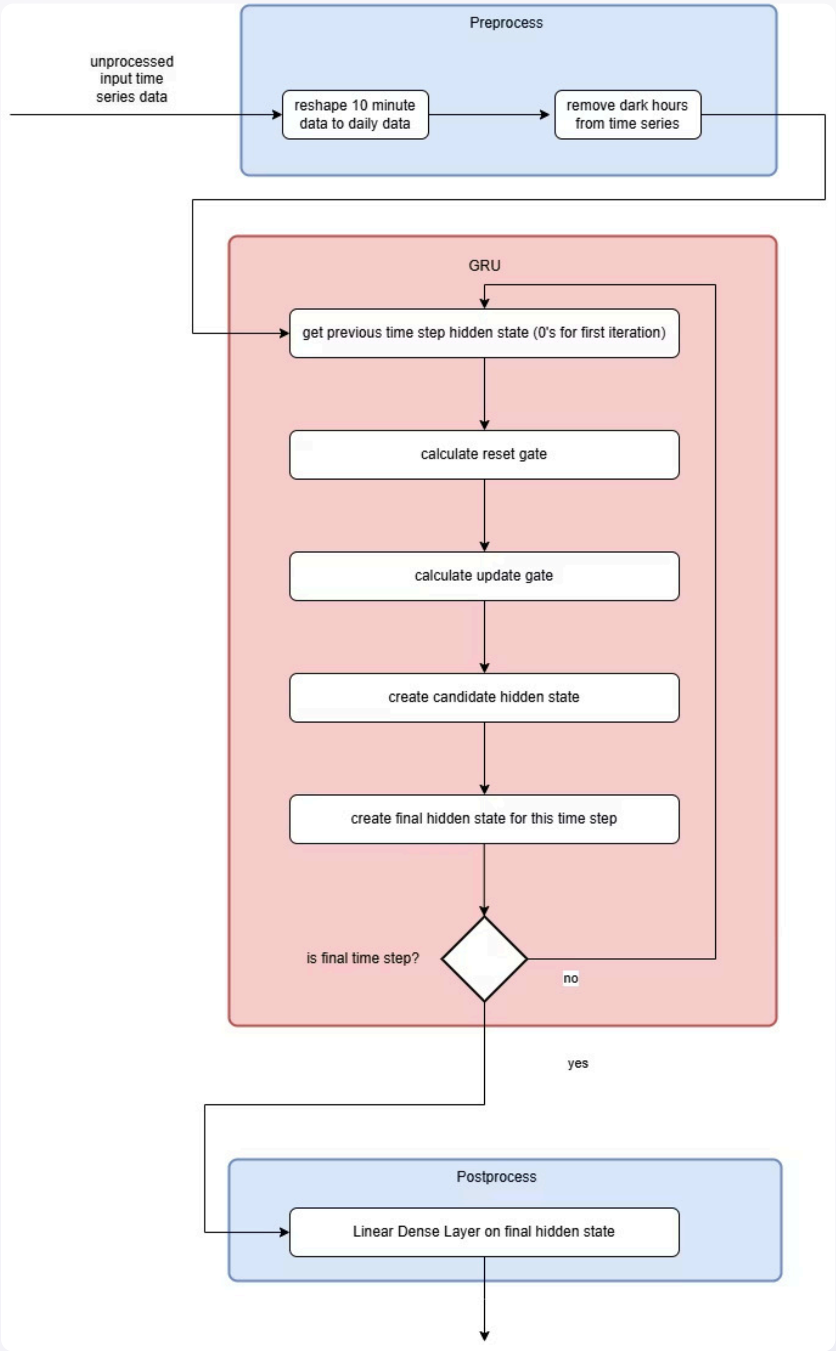
- Reset gate: Controls information retention
- Update gate: Balances new vs. previous information
- Candidate state: Generates memory proposals
- Final state: Combines via gating mechanism

Target

Hourly predictions for next 24 hours



GRU Architecture Diagram



Long-Term Forecasting: Autoformer Architecture

Autoformer Design

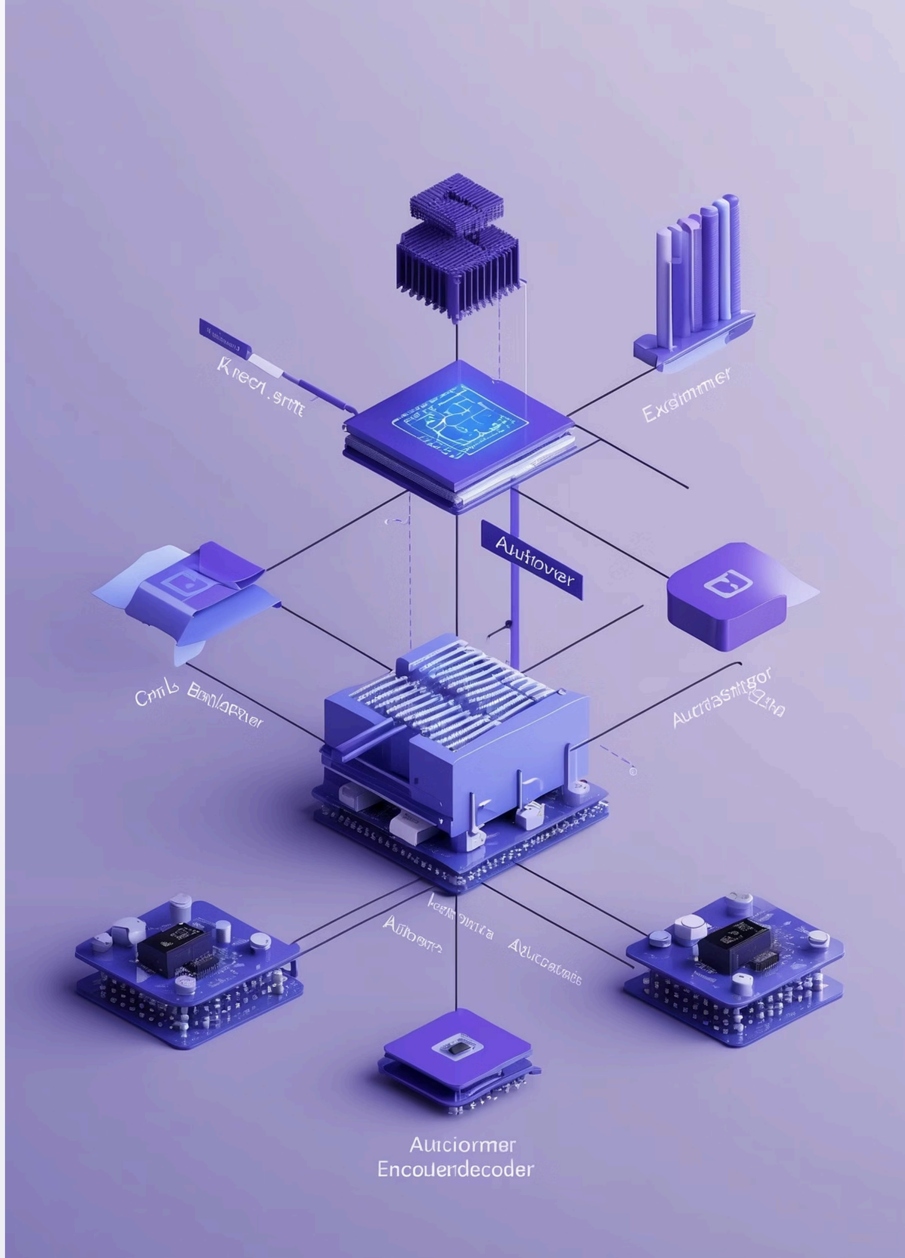
- 4 encoder layers, 2 decoder layers
- Autocorrelation mechanism replaces attention
- Series decomposition for trend/seasonal separation

Key Mechanisms

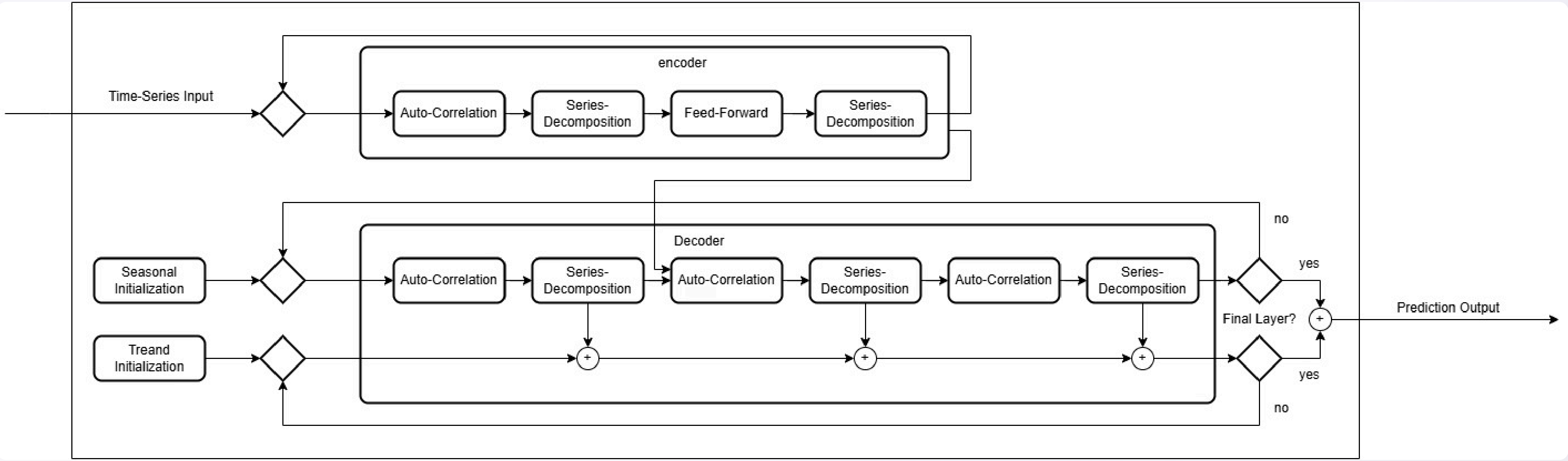
- Auto-correlation: Identifies recurring patterns
- Moving average pooling: Extracts trend components
- Cross-attention: Encoder-decoder information exchange

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

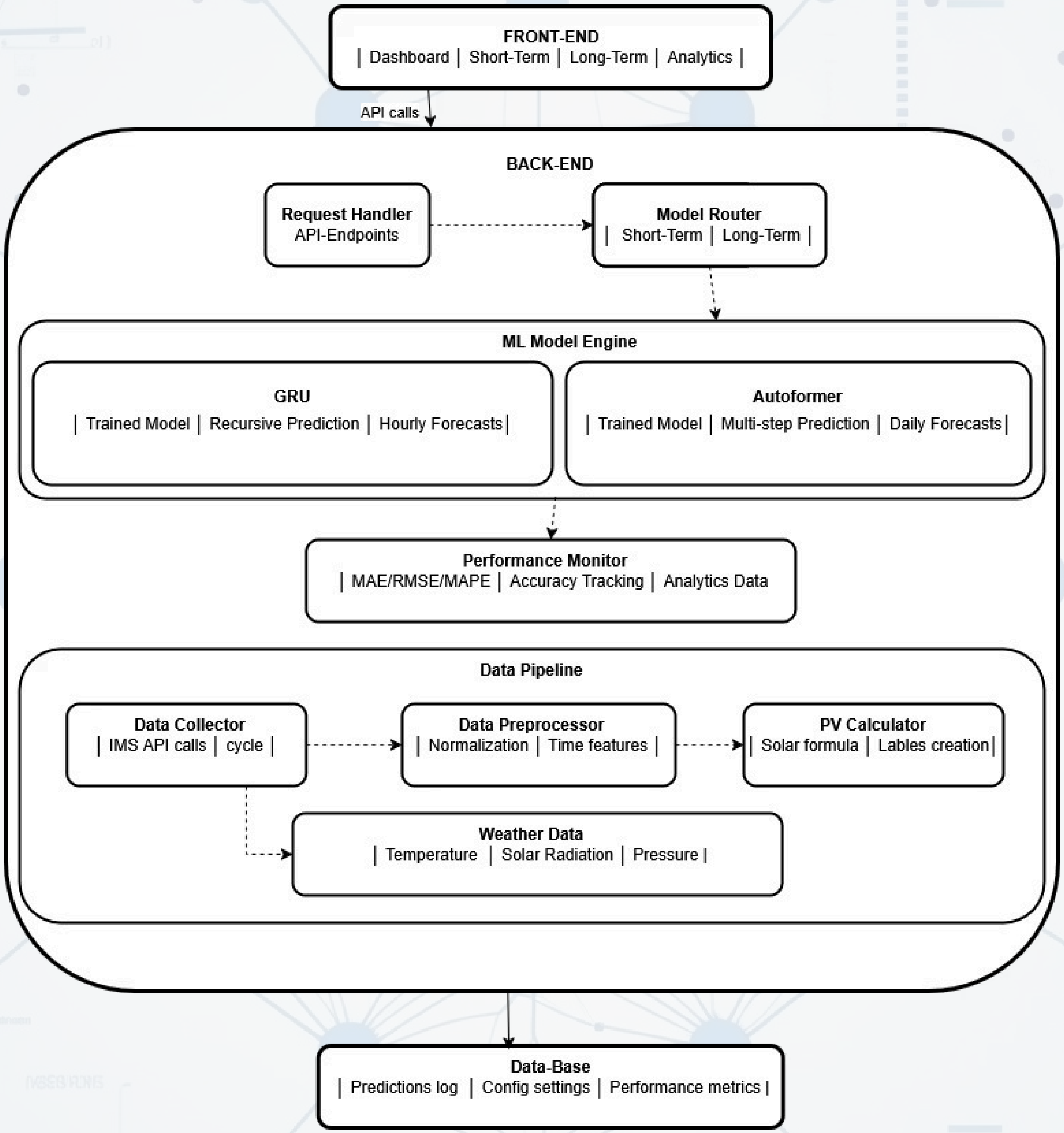
4. Prediction

Generation and delivery

5. Monitoring & 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


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/m²
Temperature: 24°C
Humidity: 45%
Wind Speed: 3.2 m/s
Wind Direction: 235°
Solar Energy Output Forecast
Forecast
Energy Output (kWh)
0
10
20
30
40
50
16:00
19:00
22:00
01:00
04:00
07:00
10:00
13:00
16:00
Time

Short-Term Forecast

Short-Term Solar Forecasting (Next 24 Hours)

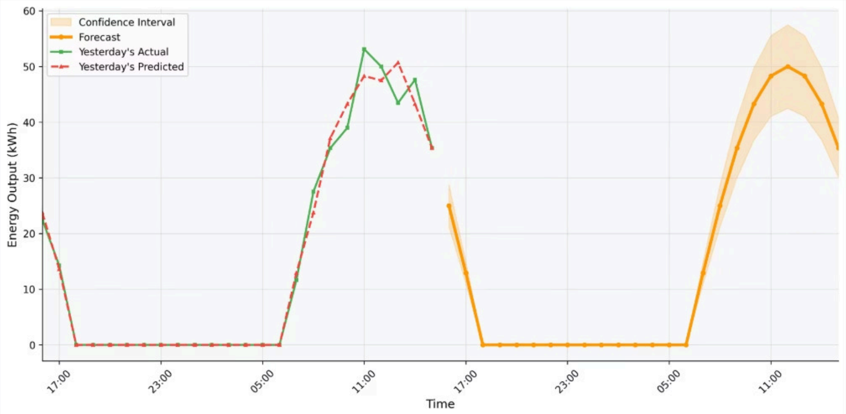
GRU Model Predictions with Confidence Intervals

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

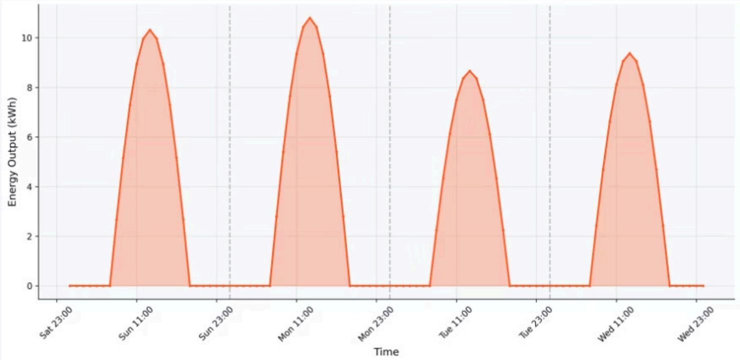
Long-Term Solar Forecasting (2-4 Days)

Autoformer Model Predictions with Seasonal Analysis

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

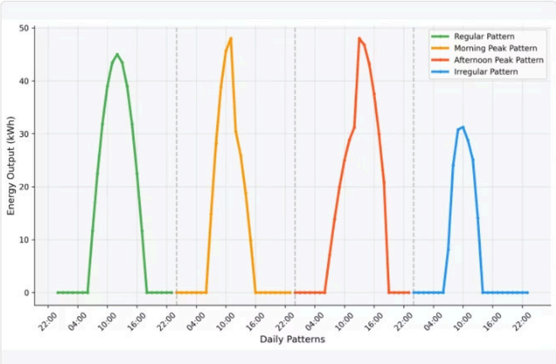
Autoformer Model Active - Multi-day predictions incorporating seasonal patterns and weather correlations.

Multi-Day Energy Forecast

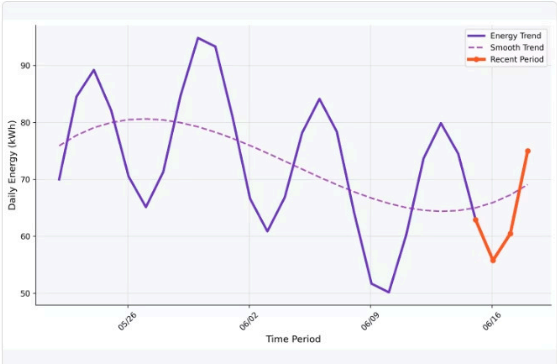


Tomorrow	Day 2	Day 3	Day 4
78.4 kWh	82.1 kWh	65.8 kWh	71.2 kWh
Peak: 12:30 PM	Peak: 1:00 PM	Peak: 11:45 AM	Peak: 12:15 PM
Confidence: 84%	Confidence: 79%	Confidence: 72%	Confidence: 68%

Seasonal Data



Trend Data



Performance Analytics

Performance Analytics & Model Validation

Historical accuracy metrics and model performance comparison

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

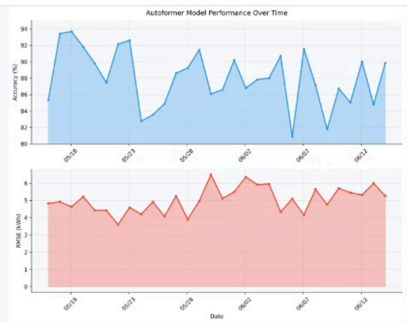
Current Model Accuracy Metrics

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)

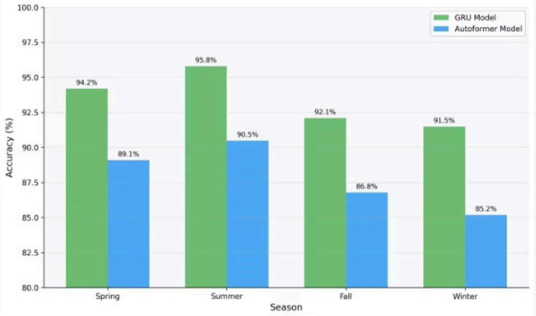
Autoformer Model (Long-term)



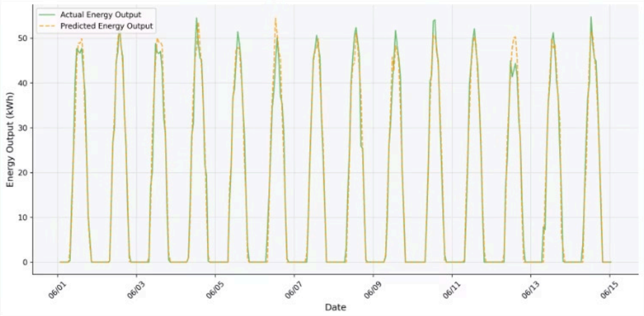
Model	Time Horizon	MAE (kWh)	RMSE (kWh)	MAPE (%)	Accuracy (%)
GRU	1-24 hours	1.89	2.76	6.4	93.6
Autoformer	2-4 days	3.12	4.85	11.8	88.2

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:

Phase 1: Data Processing

1

- 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

Phase 3: Model Integration and Evaluation

3

- 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

Phase 5: Testing and Validation

5

- 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.