Radiance Sky Image-Based Cloud Shadow Mapping for Solar Energy Forecasting

Chengdu University of Technology, Oxford Brookes Graduate Project Presentation & Defense

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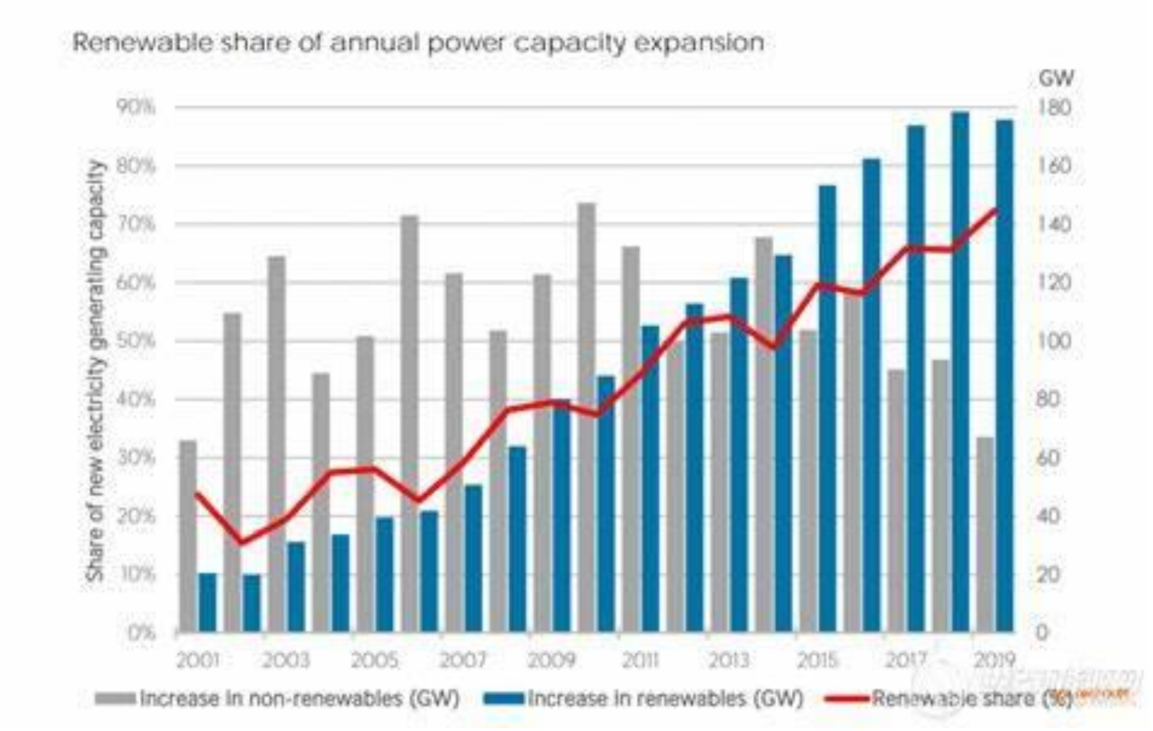
Contents

>> Background & Introduction

- Global PV Growth Challenge
- 720 TWh generated in 2019 (22% increase)
- Cloud shadows cause up to 80% power drop
- Grid stability issues from intermittency
- Need for accurate short-term forecasting



20-year PV growth rate(%), 2001-2019

Global PV growth

>> Background & Introduction

Traditional Forecasting Limitations:

1.Numerical Weather Prediction (6+ hours)
2. Physical models fail on complex patterns
3.-Limited accuracy for 5-30 minute horizon

Deep Learning Solution:
1.CNN-LSTM Hybrid Architecture
2.Attention Mechanism
3.Sky Image Analysis

>> Research Objectives

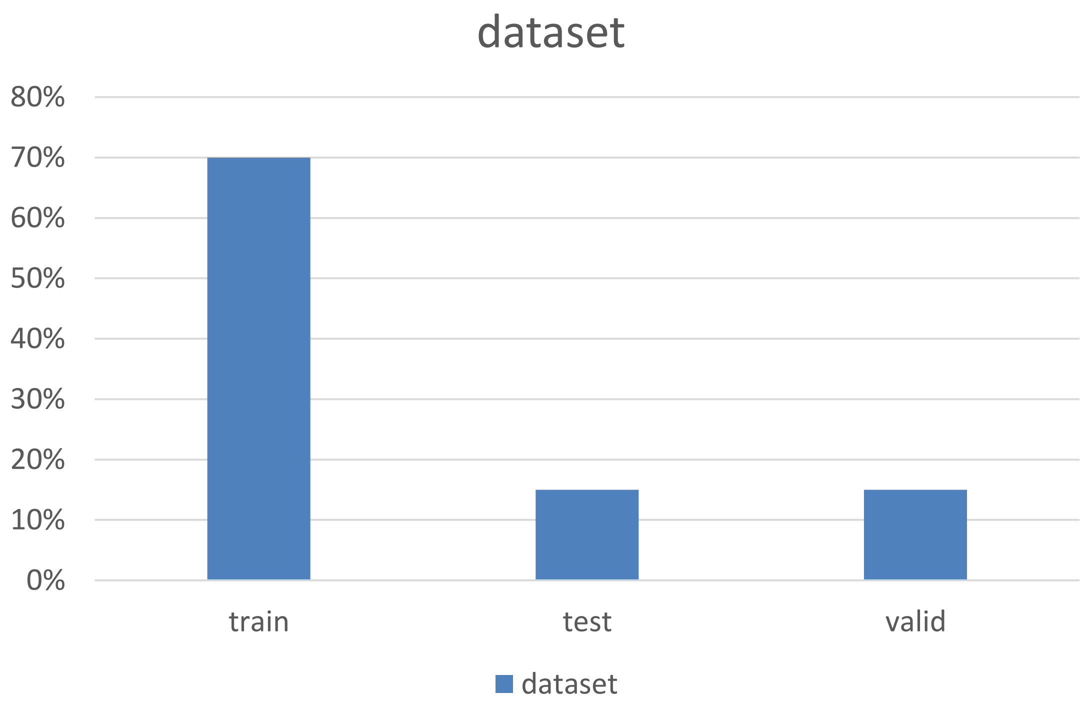
- Develop CNN-LSTM hybrid model for cloud shadow mapping
- Achieve accurate short-term (5-30 min) solar irradiance prediction
- Implement attention mechanism for improved feature extraction
- Create web-based deployment for real-time forecasting
- Enhance grid stability and renewable energy integration

>> Dataset & Methodology

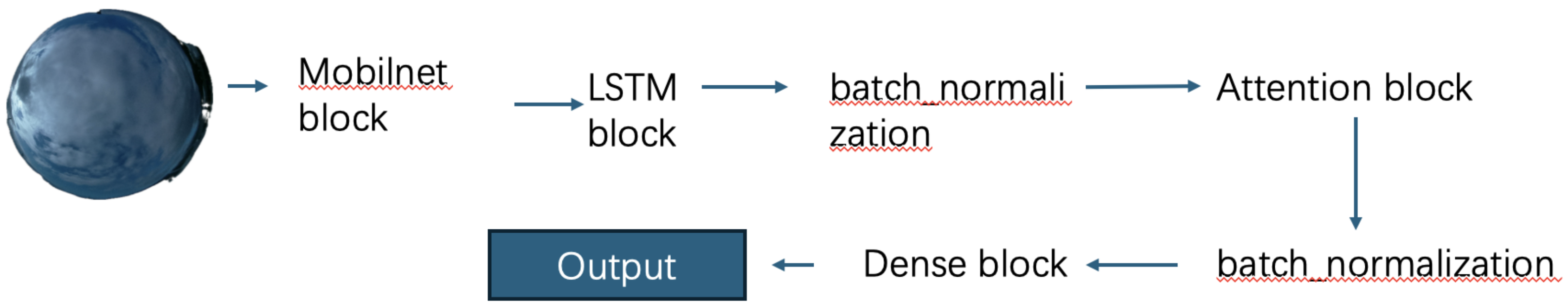
Wollongong Dataset:

- 3 locations at University of Wollongong, Australia
- Sky images (1024×768 pixels)
- 10-second intervals, 8:00 AM - 4:45 PM
- Paired with PV power measurements

Data Split:



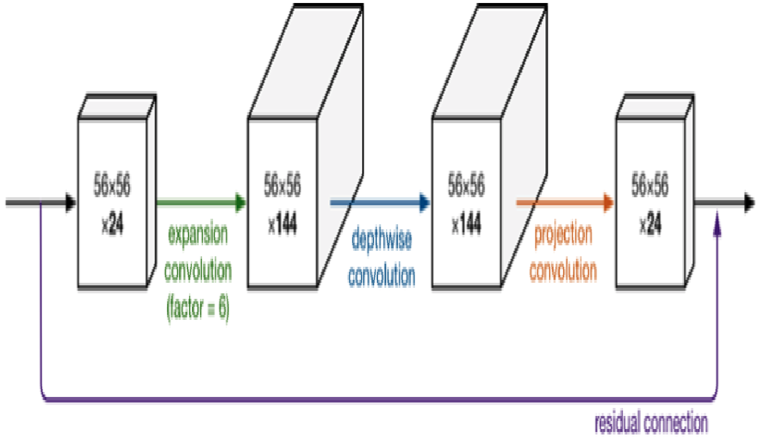
>> Proposed Model Architecture

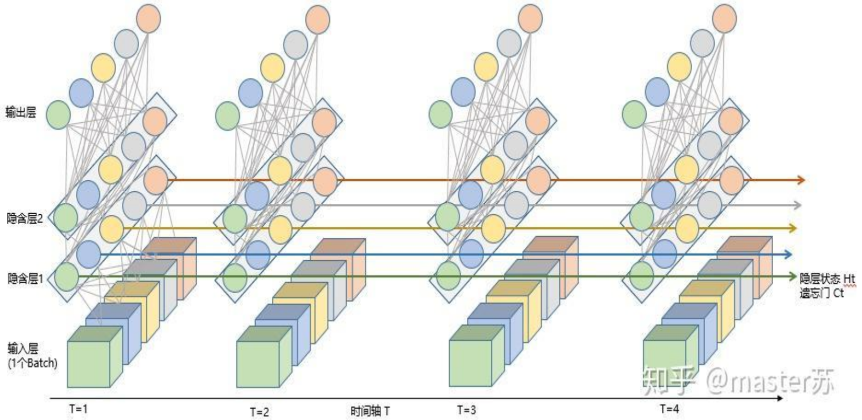


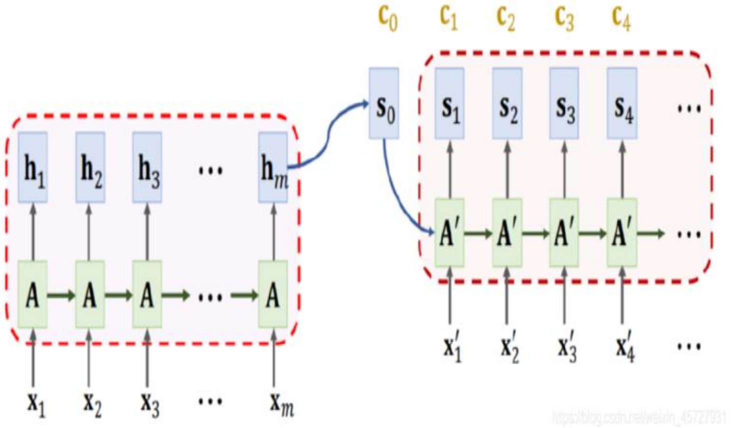
Key Components:

- MobileNet: Efficient spatial feature extraction
- LSTM: Temporal sequence modeling - Attention: Focus on relevant cloud features
- Batch Normalization: Training stability

>> Model Architecture Details







MobileNet Features:
- Input: 256×256×3
- Output: 8×8×1280 feature maps
- Depthwise separable convolutions

LSTM Configuration:
- 64 hidden units
- Dropout: 0.3
- Sequence length: 10 frames

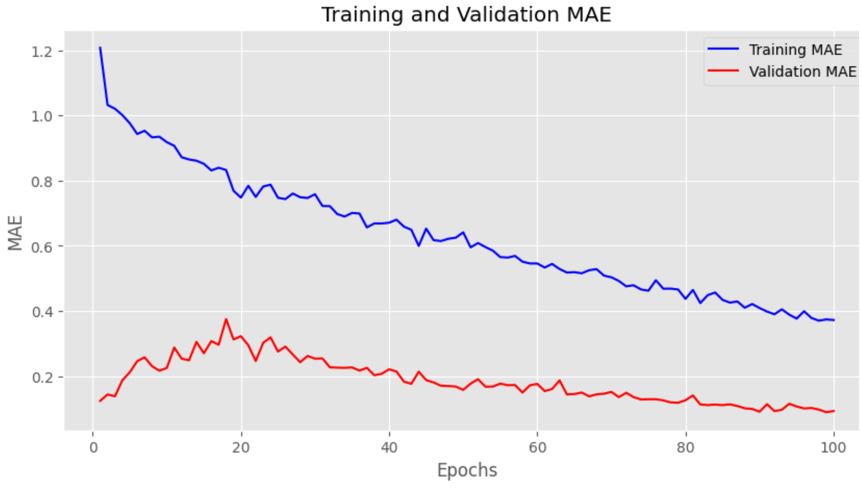
Attention Mechanism:
- Custom attention layer
- Context vector computation
- Region-based weighting

>> Training Process

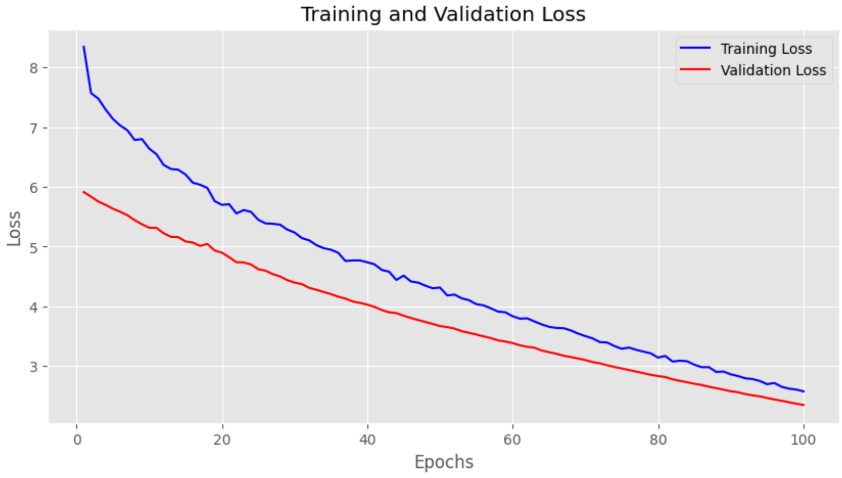
Optimization:
- Adam optimizer (lr=0.001)
- MSE loss function
- Early stopping (patience=15)
- Learning rate reduction

Regularization:
- Dropout layers (0.3)
- Batch normalization
- Data augmentation
- L2 regularization

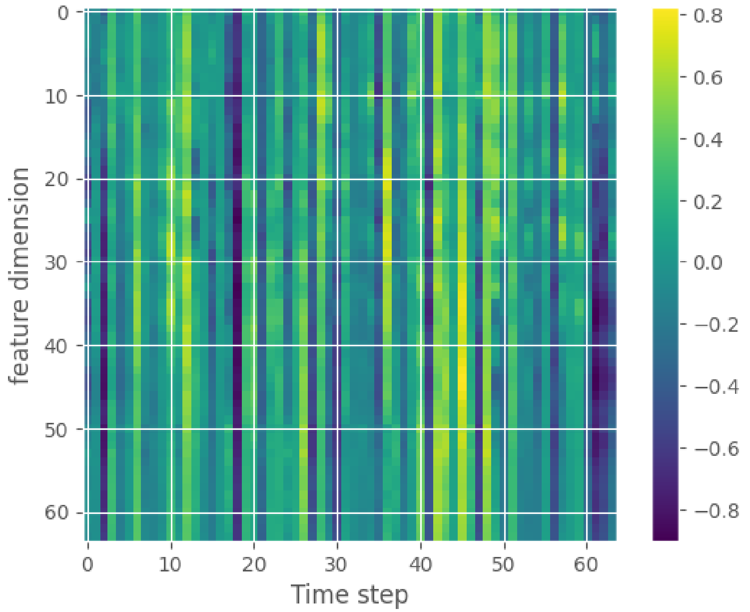
>> Results of the Proposed Model



Model MAE
Validation MAE = 0.0032



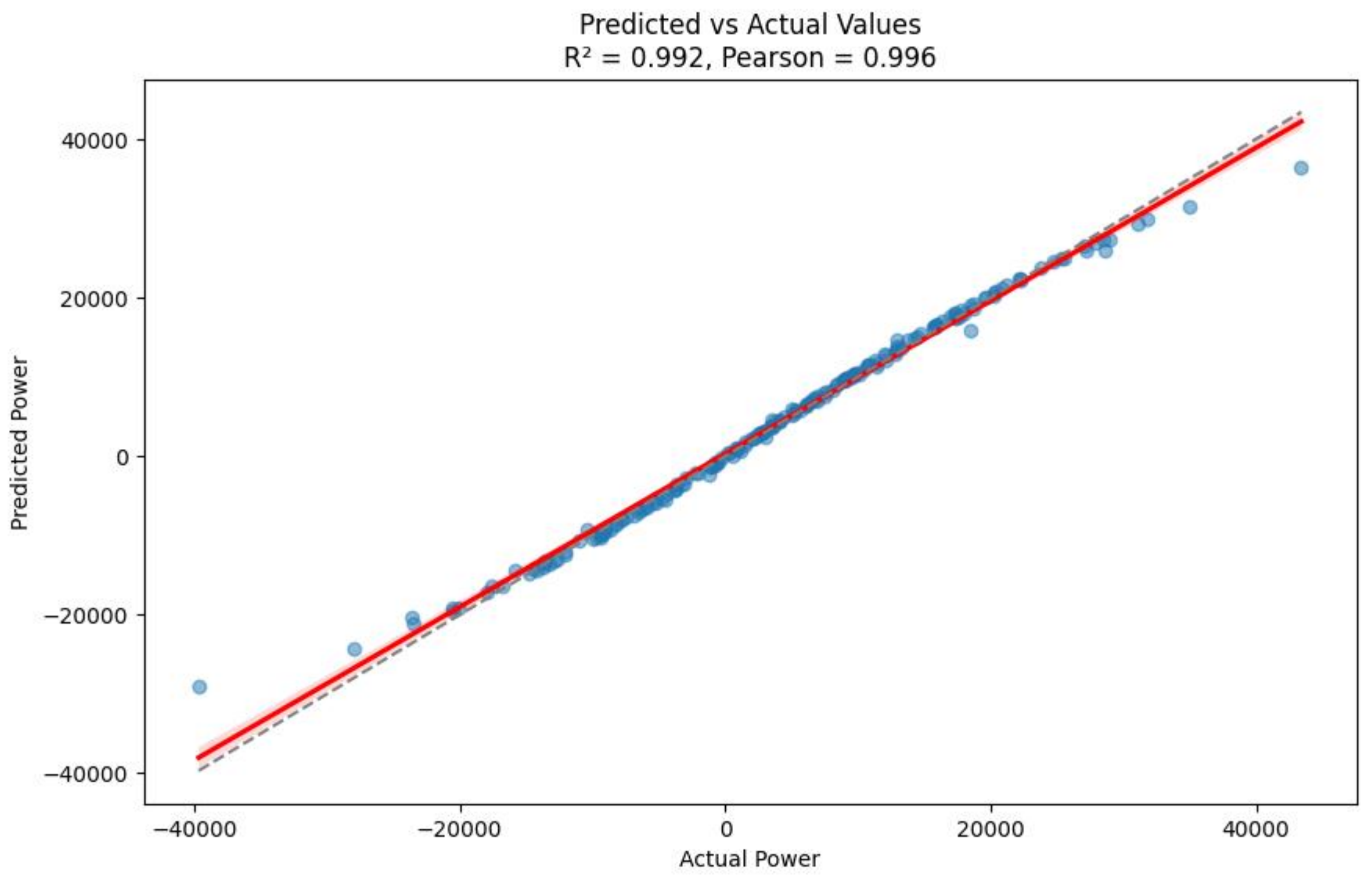
Model Loss
Validation Loss = 0.0869



Feature dimension

Performance Metrics:
- MSE: 0.0032
- MAE: 0.042
- MAPE: 17.48%
- RMSE: 0.0565
- R^2: 0.992

>> Results of the Proposed Model (cont'd)



R^2=0.992, Pearson=0.996

>> Comparison Analysis of the Proposed Model

Model	MSE	MAE	MAPE
CNN	0.0189	0.6109	314.19%
LSTM	0.0428	1.0986	438.62%
CNN-LSTM	0.0057	0.0639	28.75%
Proposed Model	0.0032	0.042	17.48%

Comparison Analysis with Previous Work

>> Comparison Analysis of the Proposed Model (cont’d)

Model	MSE	MAE	MAPE	RMSE	R^2
Proposed model	**0.0032**	**0.042**	17.48%	**0.0565**	**0.992**
CNN-LSTM (without attention)	0.0057	0.0639	28.75%	-	-
5-layer CNN-LSTM 5 层 CNN-LSTM[1]	0.006897	0.05193	-	0.08304	-
CNN-LSTM[2]	-	-	-	0.07	0.92
CNN-LSTM-RF[3]	-	0.05	-	0.07	0.92
CNN-SLSTM (optimized)[4]	-	-	**5.4315%**	6.4124%	0.9348

>> Web Application Deployment

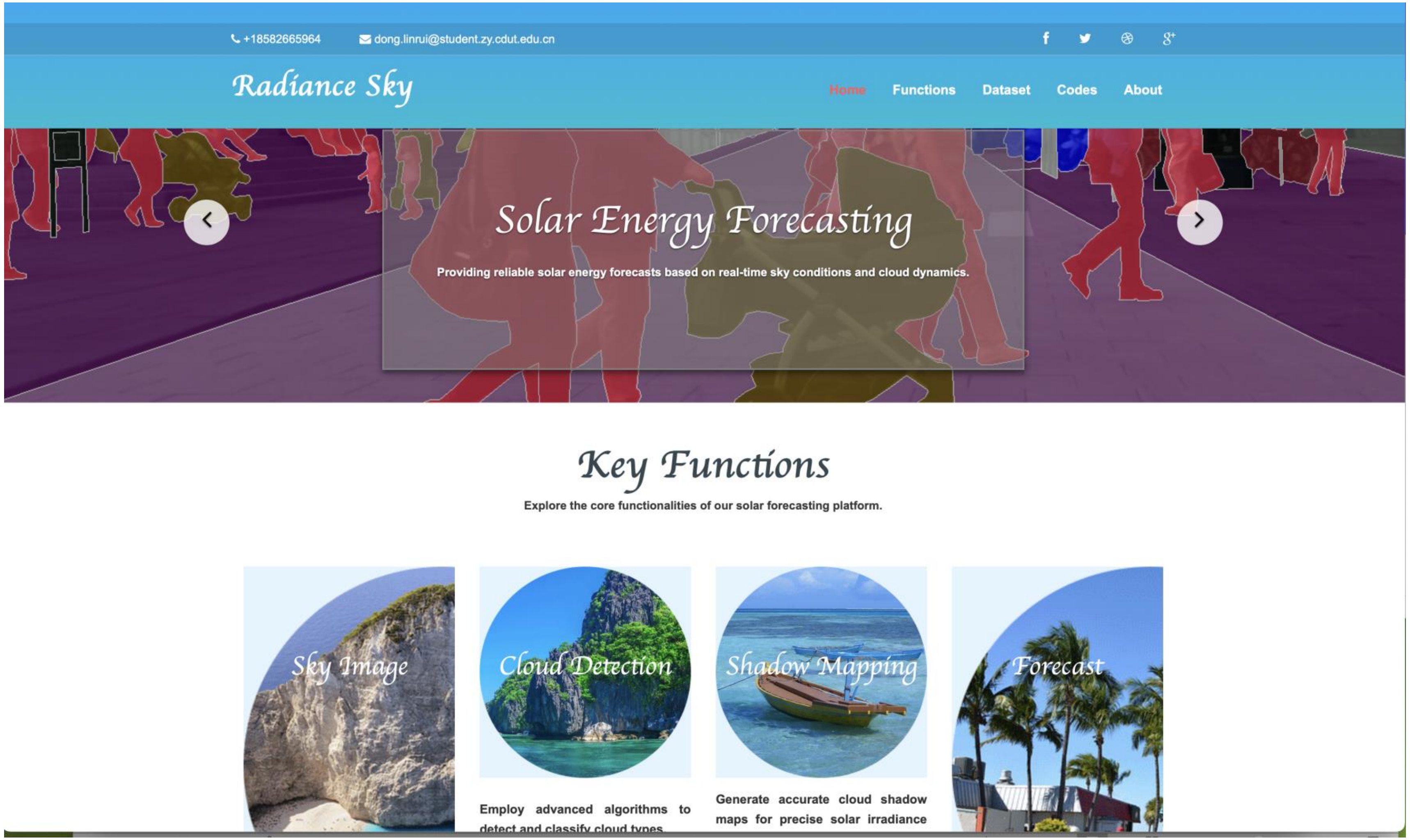


Image Uploading Zone Uploading

>> Key Contributions

Novel CNN-LSTM hybrid architecture with attention mechanism
Achieved 80%+ improvement over standalone models
Successful deployment for real-time forecasting
Contribution to renewable energy integration
Open-source implementation available

>> Conclusion

- Successfully developed hybrid deep learning model
- Achieved high accuracy (R^2 = 0.992)
- Demonstrated effectiveness across weather conditions
- Practical deployment completed
- Significant advancement in solar forecasting

>> Future Work

- Expand dataset to multiple geographical locations
- Integrate satellite imagery for enhanced coverage
- Extend prediction horizon to medium-term
- Implement ensemble methods
- Edge deployment optimization
- Integration with smart grid systems

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Thank You