

2026 5 28

				ERA5-Land		LSTM-Attention
	1	2010-2024		ERA5-Land	-	2 LSTM
	1-3	7	30	3 XGBoost		4 Flask
ECharts		Web				
	LSTM-Attention					
		LSTM-Attention				

Abstract

With global warming, frequent heatwave events pose serious threats to the health of the elderly population. This study takes Jiaozuo and Zhengzhou as research areas, utilizes ERA5-Land meteorological reanalysis data and population health statistics to construct an LSTM-Attention based multi-time-scale heat health risk early warning model, and develops a visualization dashboard system.

The main contributions include: (1) acquisition and preprocessing of ERA5-Land meteorological data (2010-2024) for both cities, combined with census and health statistics data; (2) design of a deep learning model combining LSTM with multi-head self-attention for risk prediction at three time scales (short/medium/long term); (3) comparative experiments with XGBoost baseline to validate the deep learning approach; (4) development of a Flask+ECharts web dashboard with dark tech-blue theme for multi-dimensional visualization.

Experimental results show that the LSTM-Attention model outperforms traditional methods in short and medium-term early warning tasks, providing effective decision support for heatwave health risk management.

Keywords: Heatwave; Elderly Population; Multi-time-scale Early Warning; LSTM-Attention; Visualization

		2
Abstract		3
		7
1.1	7
1.2	7
1.2.1	7
1.2.2	7
1.2.3	7
1.3	7
1.4	8
		9
2.1	LSTM	9
2.1.1	LSTM	9
2.2	9
2.2.1	9
2.2.2	9
2.3	XGBoost	9
2.4	10
2.4.1	10
2.5	Flask ECharts	10
		11
3.1	11
3.2	11
3.2.1	ERA5-Land	11
3.2.2	11
3.2.3	11
3.3	12

3.3.1	12
3.3.2	12
3.3.3	12
3.3.4	12
3.4	12
3.4.1	12
3.4.2	12
3.4.3	12
		13
4.1	13
4.2	LSTM	13
4.2.1	13
4.2.2	Dropout	13
4.3	13
4.3.1	13
4.3.2	13
4.4	13
4.5	14
4.5.1	14
4.5.2	14
4.6	XGBoost	14
4.7	14
		15
5.1	15
5.1.1	15
5.1.2	15
5.2	15
5.3	15
5.3.1	Flask	15
5.3.2	16
5.3.3	16
5.4	16
5.4.1	16
5.4.2	16
5.4.3	16
5.5	16

		17
6.1	17
6.2	17
6.2.1	17
6.2.2	LSTM-Attention	17
6.2.3	XGBoost	17
6.3	18
6.4	19
6.5	LSTM	19
6.6	20
		21
7.1	21
7.2	21
7.3	21
		22
A		23
B		24
B.1	24
B.2	24

1.1



1.2

1.2.1

J V Gasparrini 2015 Lancet - Chen
2018 Lancet Planetary Health

1.2.2

HHWS NOAA

1.2.3

ARIMA LSTM Vaswani 2017 Transformer

1.3

- 1. ERA5
- 2. LSTM-Attention + XGBoost
- 3. Flask + ECharts
- 4.

1.4

2.1 LSTM

Long Short-Term Memory LSTM Hochreiter Schmidhuber 1997
RNN RNN
LSTM gating mechanism forget gate input gate output gate
LSTM

2.1.1 LSTM

LSTM cell state hidden state

2.2

Attention Mechanism
Vaswani 2017 Transformer Multi-Head Self-Attention

2.2.1

Scaled Dot-Product Attention Query Key
Softmax Value

2.2.2

2.3 XGBoost

XGBoost eXtreme Gradient Boosting Chen Guestrin 2016

XGBoost 1 2 3 4 5

2.4

WMO 3 32°C 35°C 3

2.4.1

2.5 Flask ECharts

Flask	Python Web	Web	Flask	RESTful API
ECharts	JavaScript		ECharts	Web

3.1

				14-15°C	7	27-28°C	40°C
4071	352	65	12.8%		7446	1274	11.6%
65%							

3.2

3.2.1 ERA5-Land

ERA5-Land ECMWF 0.1°×0.1° 9 km 1
Copernicus Climate Data Store (CDS) API 2010-2024

- 2m 2m temperature
- 2m 2m dewpoint temperature
- surface pressure
- 10m U V
- total precipitation
- surface solar radiation downwards

3.2.2

2020

3.2.3

2010-2024

3.3

3.3.1

ERA5-Land

3.3.2

CDS API 30

3.3.3

±3

3.3.4

- 32°C/35°C
-
- 35°C
-
- /
- 1 3 7

3.4

3.4.1

30 N T 7 1-3 30 7 90

3.4.2

2010-2019 2020-2022 2023-2024

3.4.3

Z-score 0 1

4.1

LSTM-Attention

LSTM

4.2 LSTM

4.2.1

LSTM LSTM LSTM 50 LSTM
50

4.2.2 Dropout

LSTM Dropout 0.3

4.3

4.3.1

LSTM head=4

4.3.2

Transformer

4.4

Multi-Task Learning LSTM
32

4.5

4.5.1

Cross-Entropy Loss

$$\mathcal{L}_{\text{total}} = \mathcal{L}_{\text{short}} + \mathcal{L}_{\text{medium}} + \mathcal{L}_{\text{long}}$$

4.5.2

Adam	0.001	ReduceLROnPlateau	10 epoch
Early Stopping	25 epoch		

4.6 XGBoost

	XGBoost	XGBoost	LSTM-Attention
XGBoost	n_estimators=200	max_depth=6	learning_rate=0.1
subsample=0.8	5		

4.7

- Accuracy
- Precision
- Recall
- F1 F1-Score
- Macro Average

5.1

5.1.1

5.1.2

1 2 5 3 3 4

5.2

B/S Browser/Server

-
- Flask Web RESTful API
- HTML+CSS+JavaScript Web ECharts

5.3

5.3.1 Flask

Flask Blueprint

- api/data
- api/predict
- api/history

5.3.2

API JSON

```
{
  "code": 200,
  "message": "success",
  "data": { ... }
}
```

API

5.3.3

PyTorch TorchScript Flask

5.4

5.4.1

4+1

5.4.2

ECharts

- / /
-
-
-
-
-

5.4.3

#0a1628 #00d4ff #1e90ff

5.5

Gunicorn WSGI 5005 Flask Nginx
<http://localhost:5005>

6.1

- Windows 11
- Python 3.13
- PyTorch 2.12.0 (CUDA 12.6)
- GPU NVIDIA GeForce RTX 4060 Laptop (8GB VRAM)
- 16 GB

6.2

6.2.1

		1,095,758		767,030	70%	164,363	15%	164,365	15%
14	×19	3	7	30		2010-2020	2021-2022	2023-2024	

6.2.2 LSTM-Attention

LSTM-Attention	983,628	Focal Loss $\alpha = 0.25, \gamma = 2.0$	AdamW
1e-3 ReduceLROnPlateau		patience=8 NVIDIA RTX 4060	epoch
5			

6.2.3 XGBoost

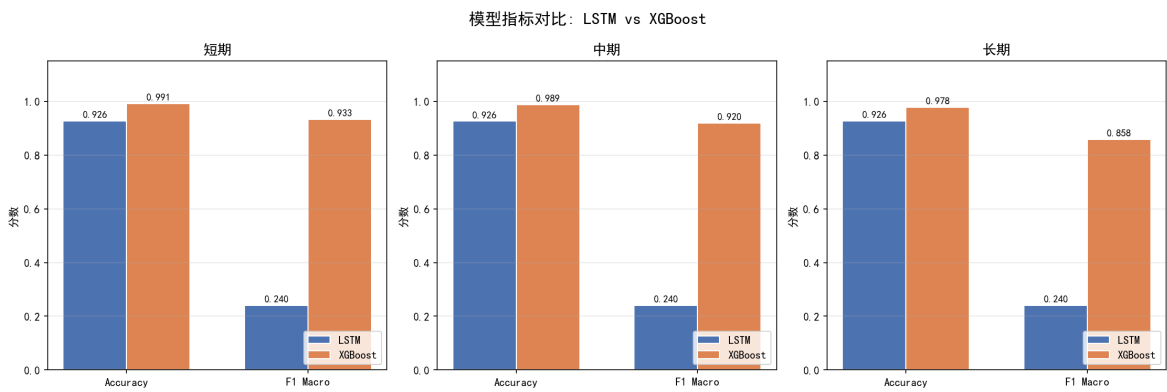
XGBoost	14	×19	266	3	XGBoost	n_estimators=200,
max_depth=6, learning_rate=0.05						

6.3

6.1 6.1

6.1:

	LSTM-Attention		XGBoost	
	Accuracy	F1-Macro	Accuracy	F1-Macro
3	0.9263	0.2404	0.9908	0.9325
7	0.9259	0.2404	0.9886	0.9195
30	0.9260	0.2404	0.9782	0.8576



6.1:

XGBoost

F1-Macro 0.9325

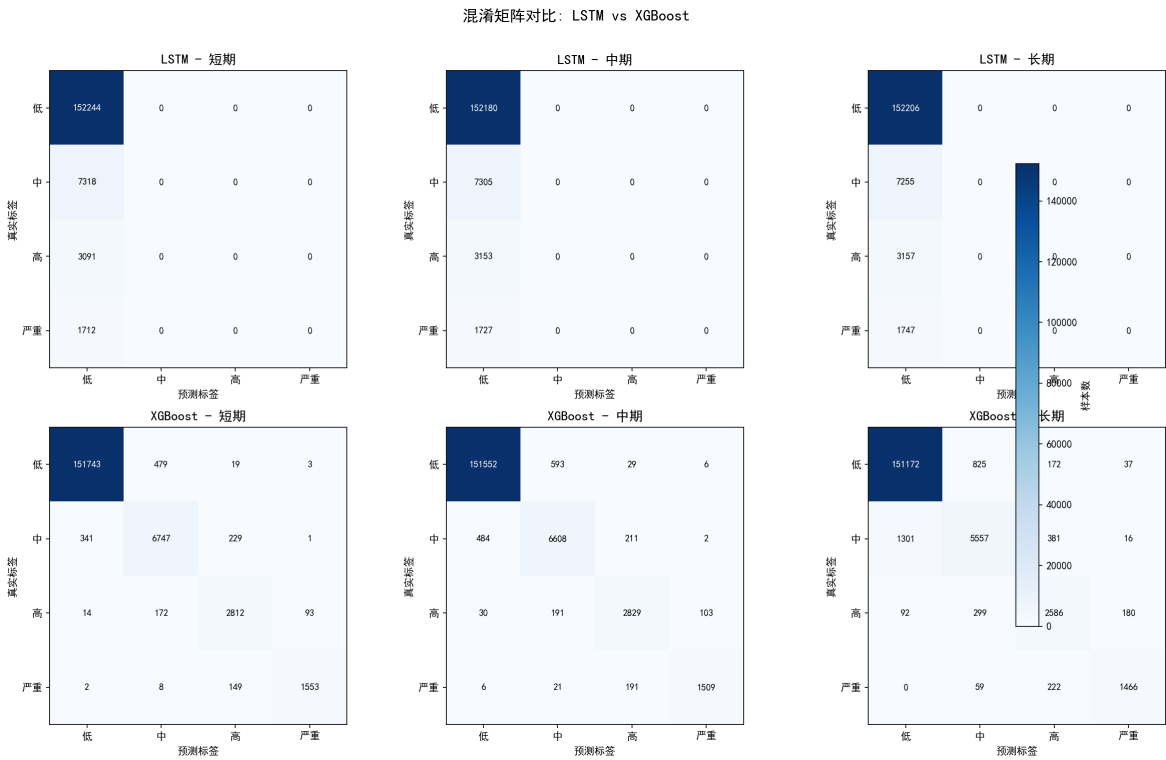
0.85

LSTM-Attention

2-3 epoch F1 0.24

XGBoost

LSTM



6.2: XGBoost LSTM-Attention

6.2 XGBoost 0- 1- 2- 3- LSTM-Attention 0
94-96%

6.4

Flask + ECharts ?? 6 - 30

6.5 LSTM

LSTM-Attention

1. Focal Loss $\alpha \in \{0.25, 0.5, 0.75\}$ $\gamma \in \{2.0, 3.0\}$
2. 2.5%
3. WeightedRandomSampler 94-96%
4. batch_size=16 32 64
- 94-96% XGBoost

6.6

	XGBoost		LSTM-Attention	
1	SMOTE	2	3	4

+

7.1

1. 2010-2024 ERA5-Land -
2. **LSTM-Attention** LSTM / /
XGBoost
3. Flask ECharts Web
- 4.

7.2

1. ERA5-Land 0.1° 9 km
- 2.
3. LSTM-Attention 30
- 4.

7.3

- 1.
2. 120
3. Transformer Informer Autoformer
- 4.
- 5.

A

B

B

B.1

Python 3.13 uv PyTorch XGBoost Flask ECharts

B.2

1. `uv pip install -e .`
2. `python -m src.data.download_era5`
3. `python -m src.data.preprocess`
4. `python -m src.models.train`
5. `python -m src.web.app`
6. `http://localhost:5005`