Identifying Overlapping Successive Events Using a Shallow Convolutional Neural Network

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Motivations of Event Identification

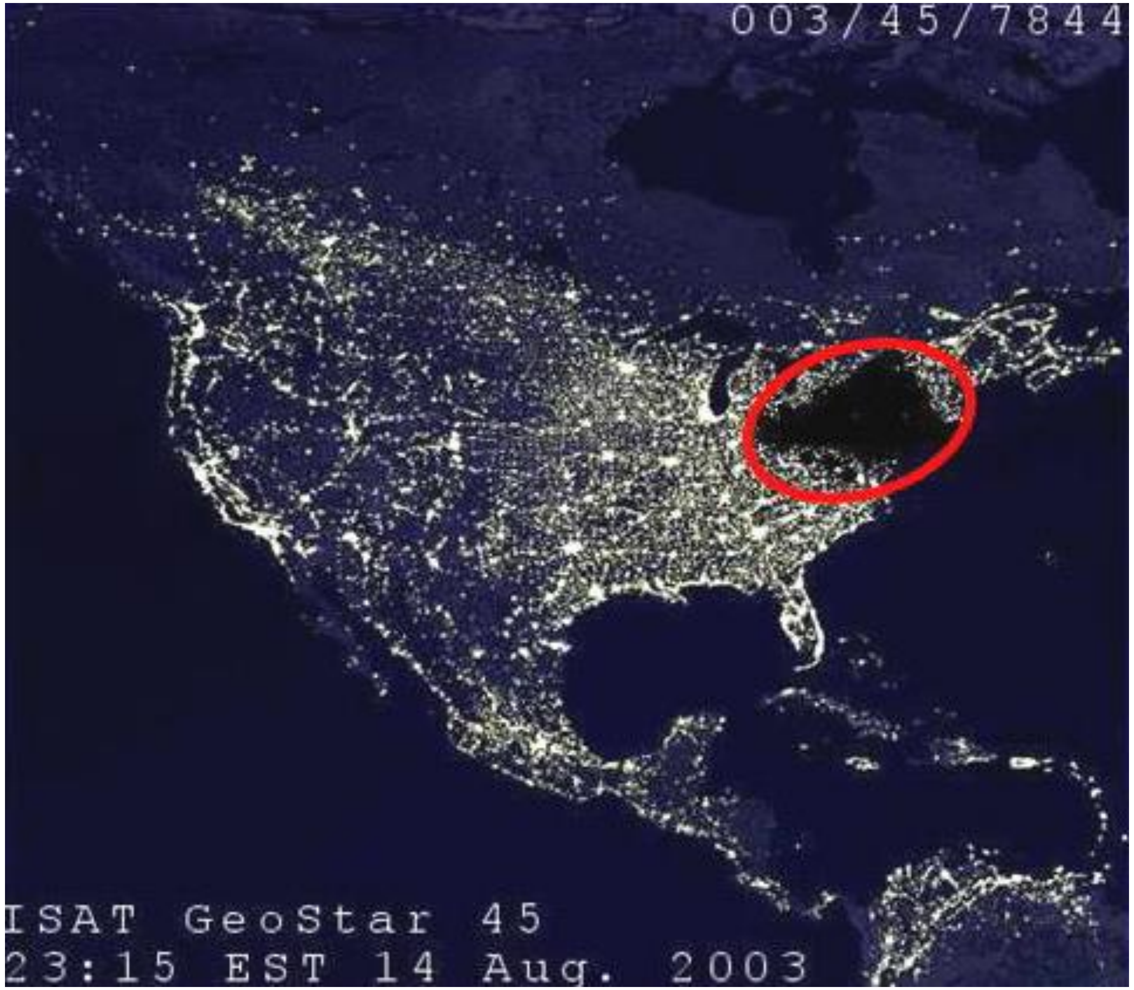

Fig. 1 The satellite photograph shows the blackout in 2003
https://www.snopes.com/fact-check/blackout-2/

- Efficiently identifying large events are beneficial to **avoid blackout** and improve power system **stability and reliability**;
- More than **2000** Phasor measurement units (PMUs) have been installed in the United States;
- A number of PMU data motivate people to monitor and control power system with **data-driven** methods.

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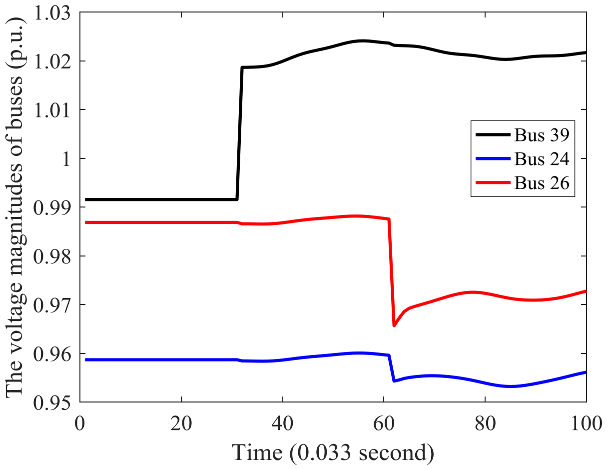
Existing Approaches

- Recent development of event identification methods[1-5]:
- Advantages:
  - model-free, robust to model errors.
- Limitations:
  - **Single events** or multiple events with long time intervals and minor overlapping;
  - A **large number** of training datasets;
  - No clear **physical interpretations;**
  - High training **complexity.**

Challenges of Identifying Successive Events



(a)

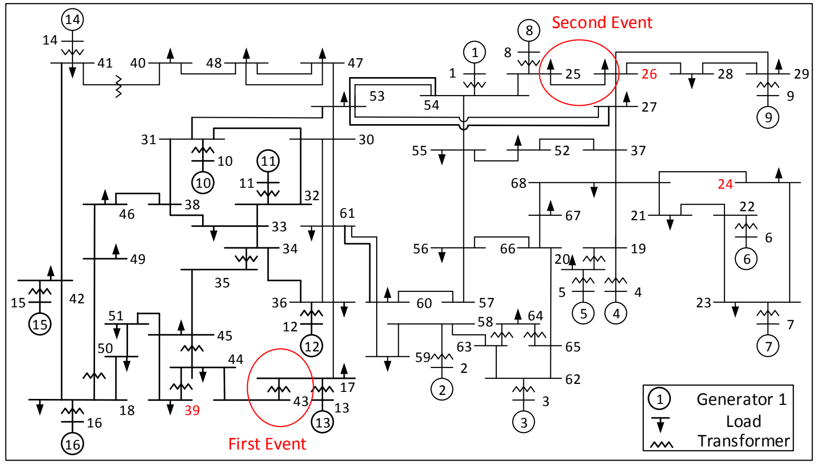


Fig. 3 (a) Line 17-43 tripped at 1 s followed by line 25-26 tripped event at 2 s in the IEEE 68-bus power system.

- The two successive events in (a) are almost independent,

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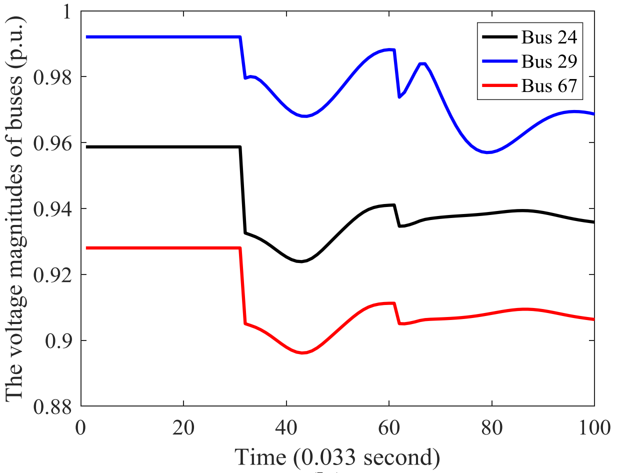

(b)

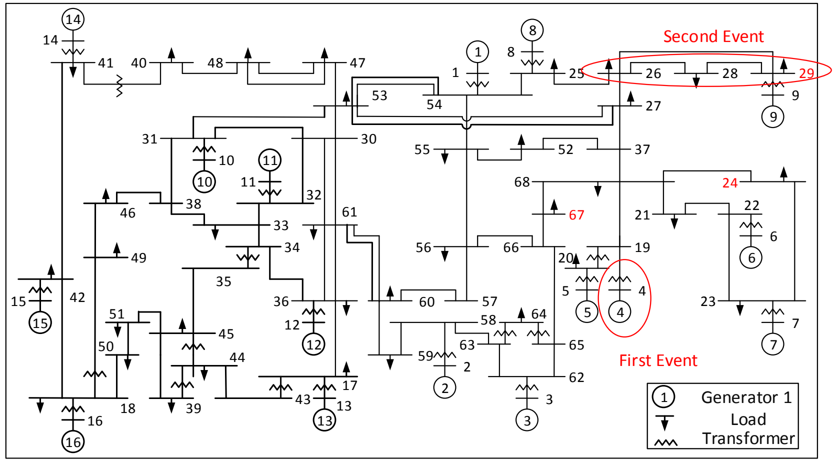

Fig. 4 (b) Generator at bus 4 tripped at 1 s followed by line 26-29 tripped at 2 s in the IEEE 68-bus power system.

- The two successive events in (a) are almost independent, but the successive events in (b) **are overlapping**;
- **Insufficient** number of historical successive events for training;
- **Goals**
    - Offline training of **single events**
    - Online identification of **overlapping** successive events

Definition of Dominant Features

- Dominant Features:
  - $M_1^T = [y_1, \ldots, y_T]$ is a data matrix of m PMU channels in T,
    $$M_1^T \approx U_r \Sigma_r V_r^\dagger$$
    - $U_r, V_r \in C^{m \times r}$ $\Sigma_r = diag(\sigma_1, \cdots, \sigma_r)$ are singular vectors and values.
  - Since $y_t = A\, y_{t-1}$, the two data matrices in sequential windows:
    $$M_1^T = A M_2^{T+1}$$
  - Define the eigenvalues of A and $\sigma_1, \cdots, \sigma_r$ as the $\boldsymbol{dominant\ features}$.
- Classification:
  - The extracted dominant features are input to a 2-layer CNN classifier.

Offline Training

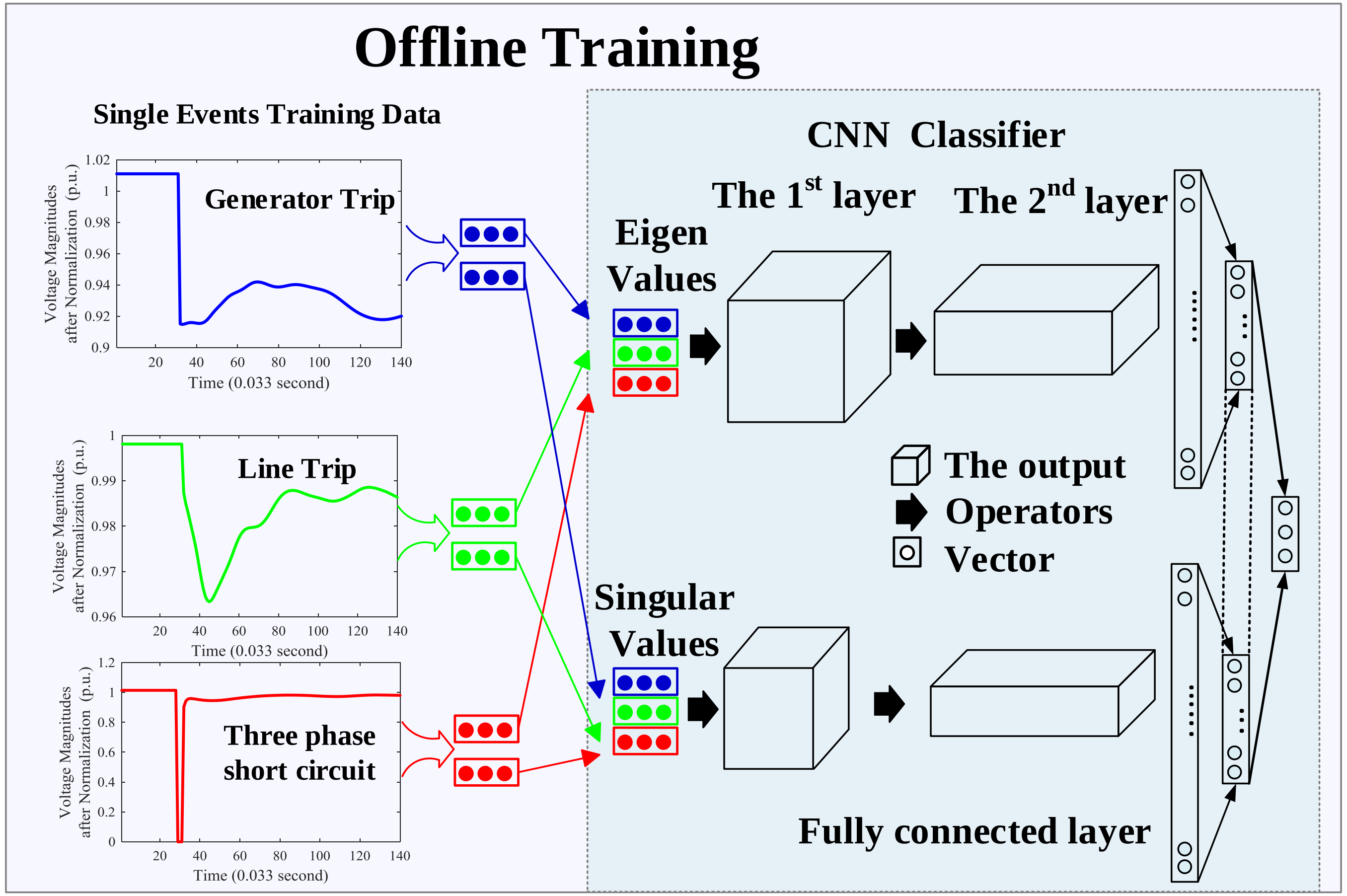

Fig. 5 Offline training on single events of Generator Trips (**GT**s), Line Trips (**LT**s), and Three phase short circuit (TPs)

- Extract dominant **Eigen values** $\boldsymbol{\lambda}$ of the state matrix and **singular values** $\boldsymbol{\sigma}$ of the recorded single events as features;
- Input featrures (λ, σ) to a 2-layer CNN of **two-path**;
- Train the **2-layer CNN classifier** to identify the type of an event.

Online Testing

Given the two **successive events** occurring at T1 and T2 respectively, there are **three steps** to identify the type of second event:

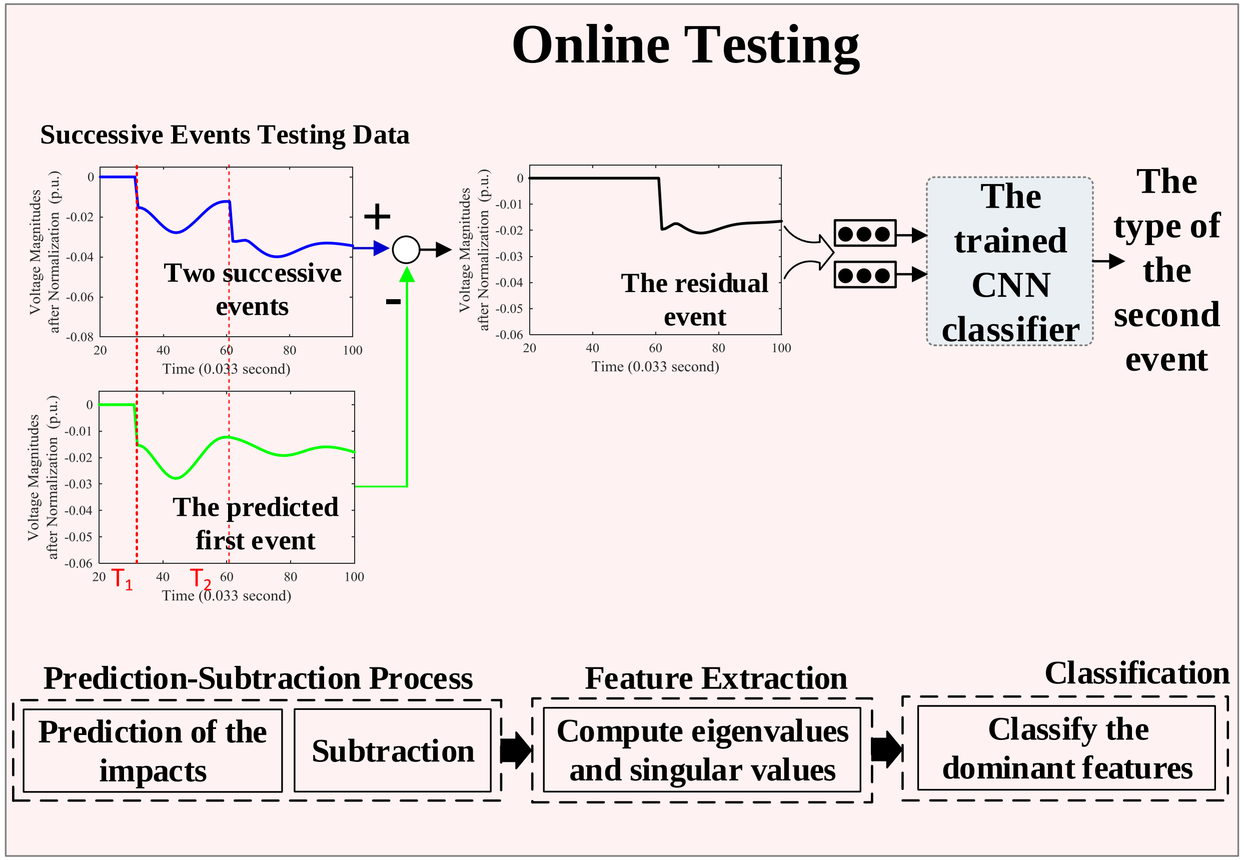

Fig. 5 Online testing of successive events through three components

- Step 1: **predict** the impact of the first event after T_2 and **subtract** it;

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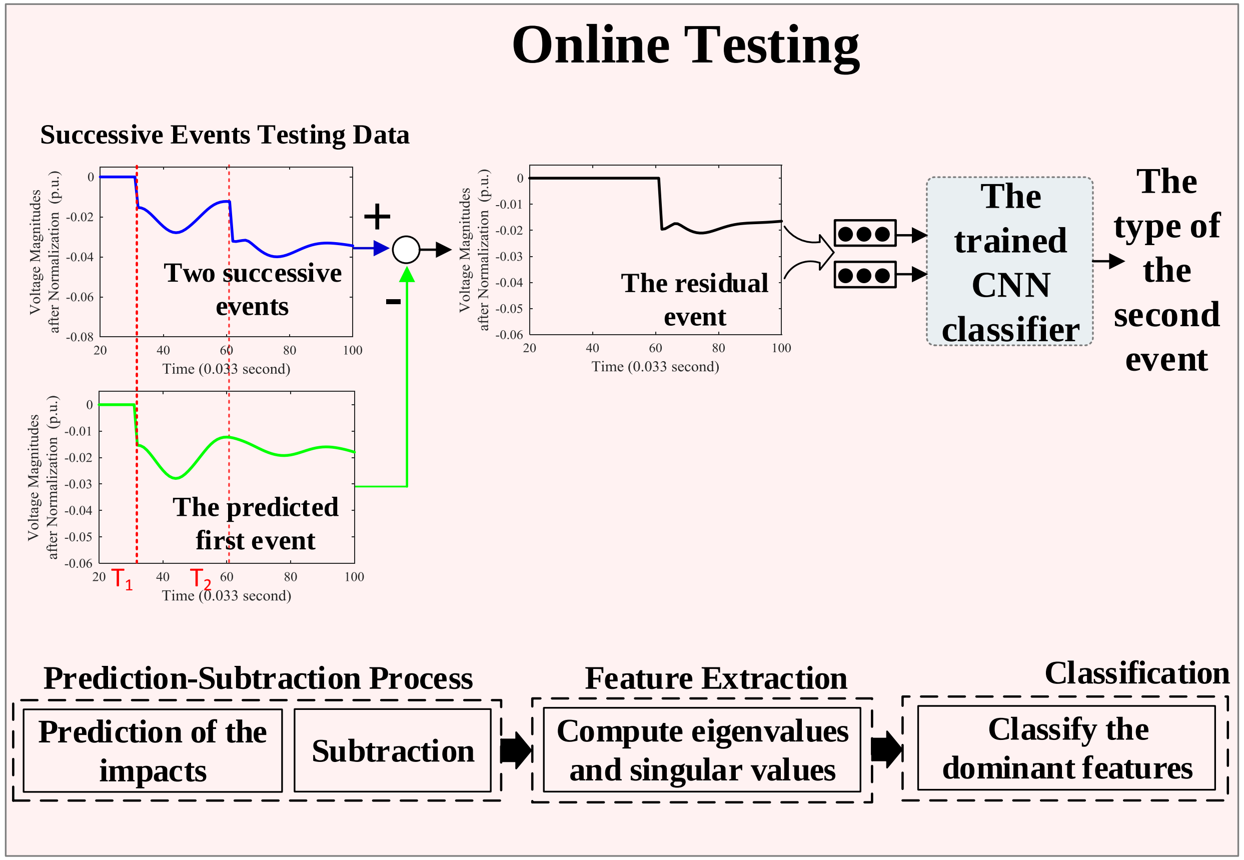

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- Various methods can be employed to predict the measurements, such as time series analysis and Hankel matrix based methods [6-7];

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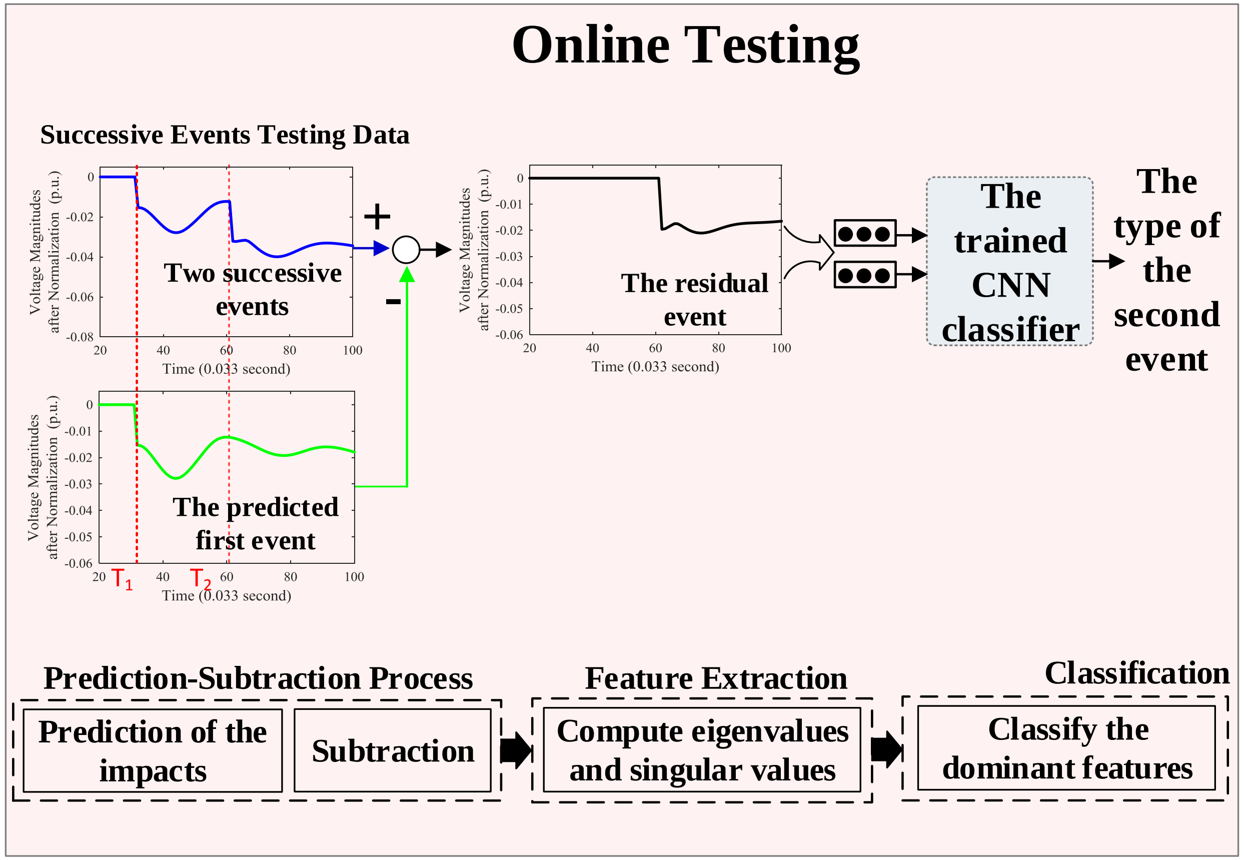

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- Various methods can be employed to predict the measurements, such as time series analysis and Hankel matrix based methods [6-7];
- We apply the prediction method based on the **dominant eigenvalues.**

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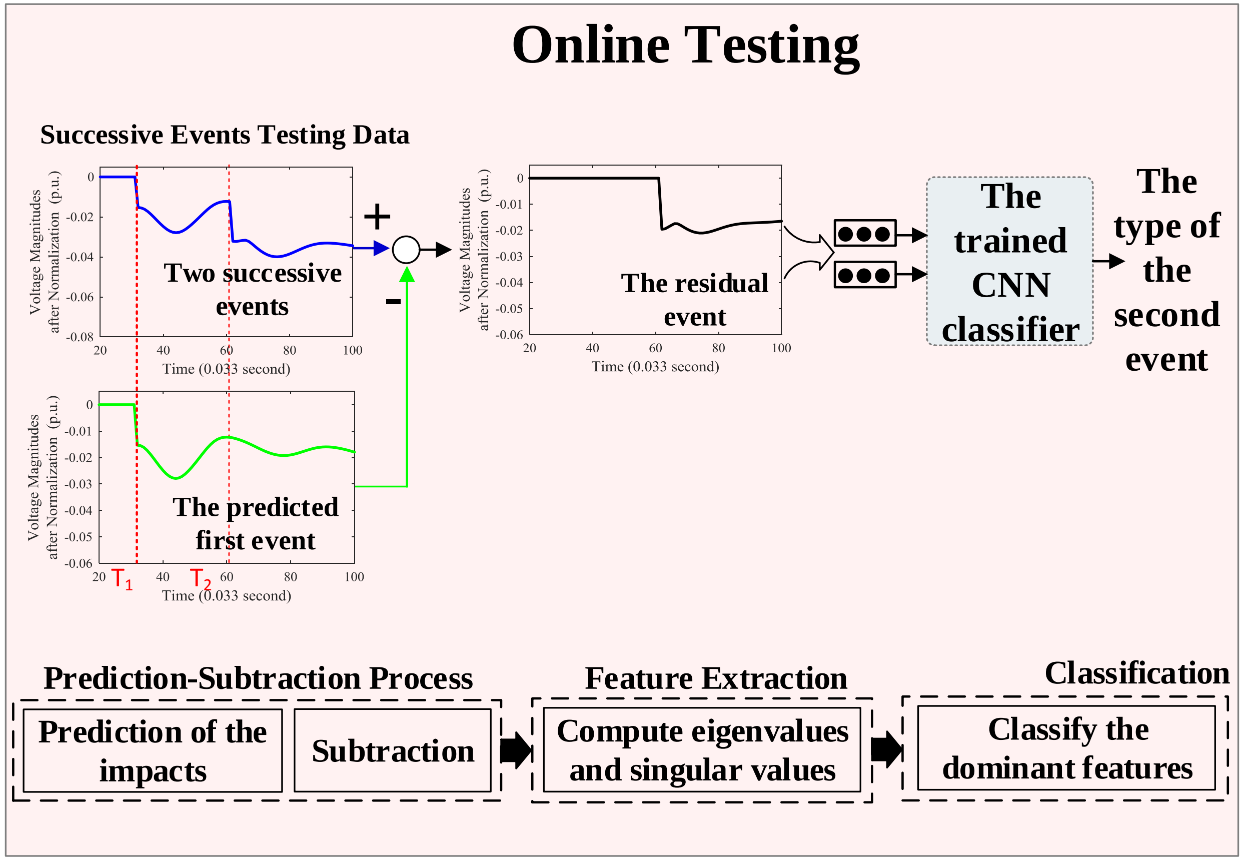

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- <u>Step 2</u>: The dominant features **(λ, σ) are extracted** from the residual measurements;

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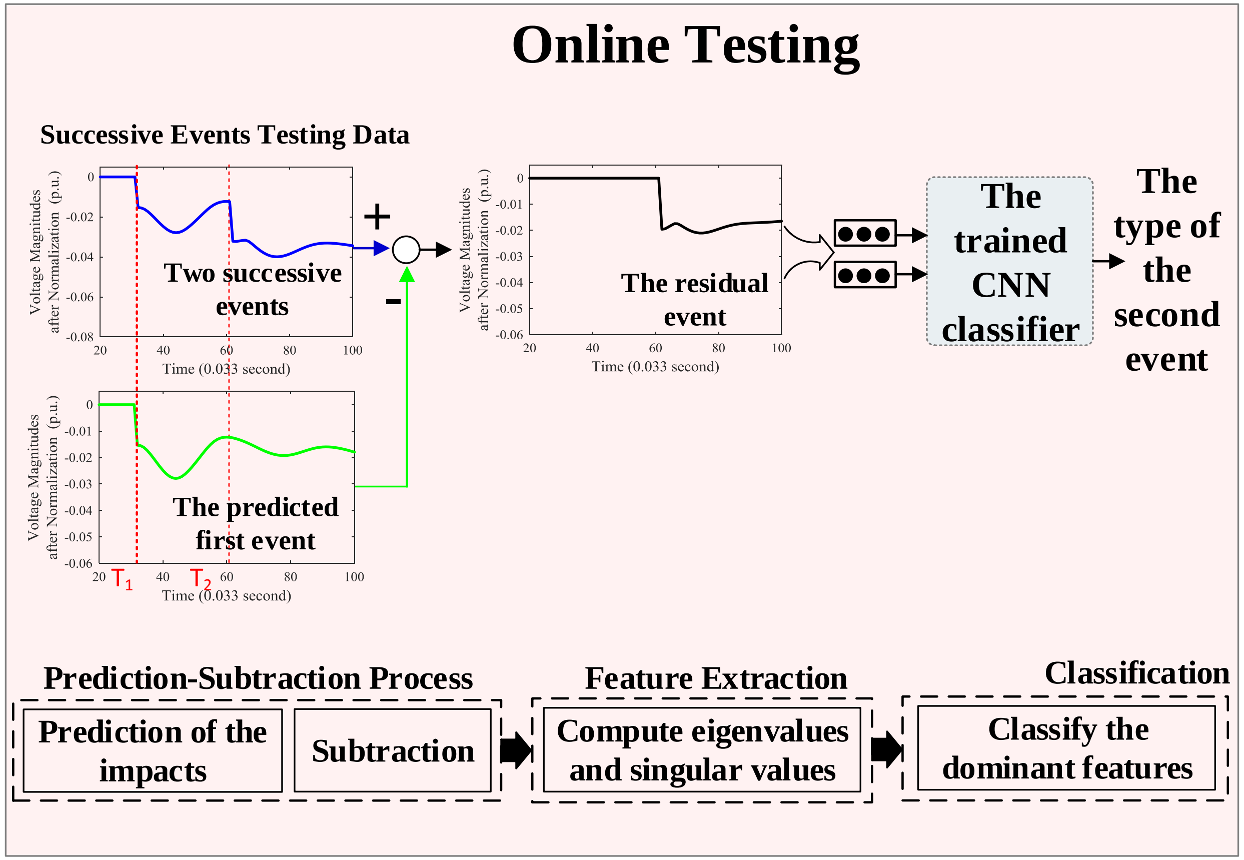

Fig. 5 Online testing of successive events through three components

- <u>Step 2</u>: The dominant features **(λ, σ) are extracted** from the residual measurements;
- <u>Step 3</u>**:** The trained **CNN outputs the type** of the second event in real time.

Numerical Results

Table 1.The Identification Accuracy Rate (**IAR**[1]) of 380 simulated datasets

IAR %	LT + GT	LT + TP	LT + LT	GT + GT	GT + TP	TP +GT
CNN-F[2]	**86.4**	**97.8**	**81.1**	**87.3**	**77.5**	**91.3**
CNN-T[3]	63.8	65.3	80.5	63.1	26.5	85.8

- Simulated datasets are generated by **PSS/E** in the IEEE 68-bus power system.
- 967 single events are employed to train the classifier, and the CNN identifies 1136 successive events of different combinations as shown in Table , where "**LT+GT**" denotes a line trip event is followed by a generator trip event.

[1]**IAR** is the ratio of the number of correctly classified events to the total number of events.

[2]**CNN-F** represents the CNN with **dominant features** as inputs.

[3]**CNN-T** represents the CNN with **time series** as inputs.

Performance with small training datasets

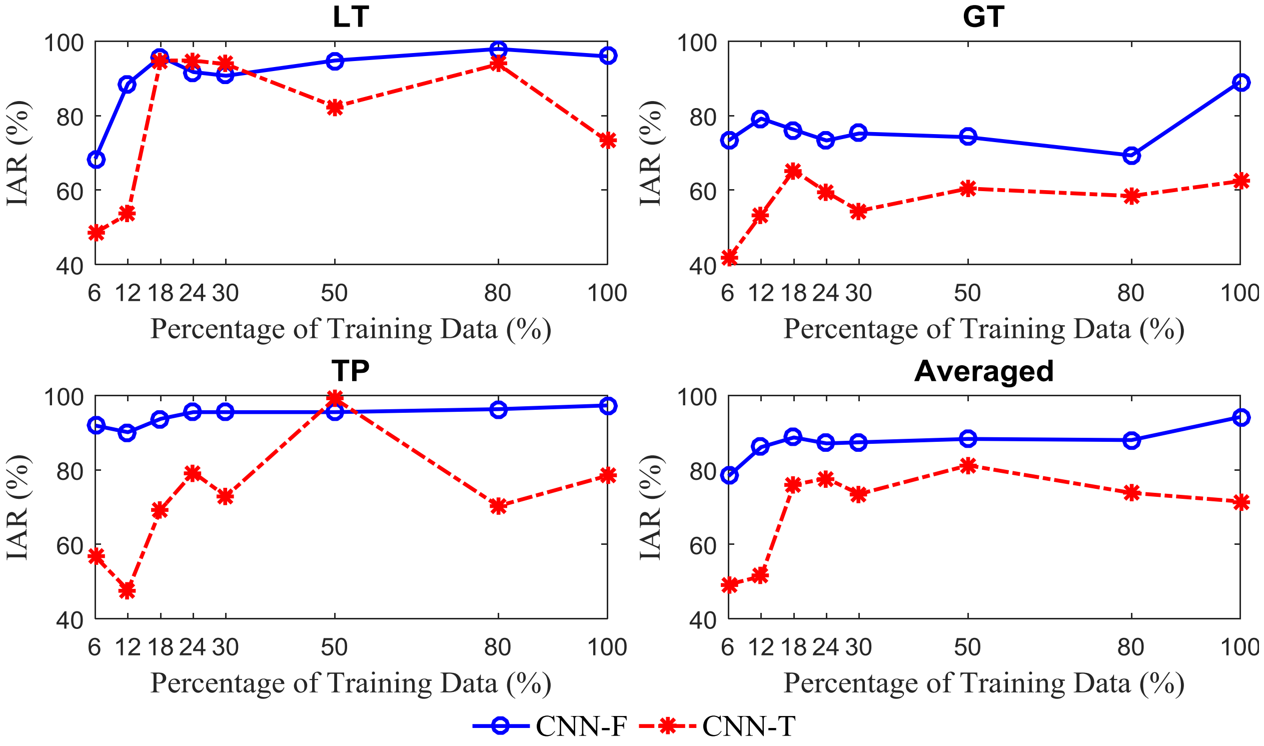

Fig. 6 The IAR of CNN-F and CNN-T when partial training datasets are available

- The dominant features are robust to initial conditions, and the **CNN-F** achieves **a higher IAR** with small training datasets.
- The IAR of **CNN-T is sensitive** to the size of the training data.

The Impact of Subtracting the First Event

Table 1. The performance comparison with and without subtracting the first event ($\Delta T = 1s$)

Classifier	Process	LT %	GT %	TP %	Overall %
CNN-F	NS	79.4	68.3	96.4	81.9
CNN-F	**SP**	**95.9**	**89.1**	**97.3**	**94.2**
CNN-T	NS	94.8	83.2	78.4	85.1
CNN-T	SP	73.2	62.4	78.4	71.5

- “Not Subtract (**NS**)” :using the data after the second event directly.
- “Subtract the Prediction (**SP**)” means using the residual data after subtracting the first event.
- Subtracting the impact of the first event can **enhance** CNN-F’s performance significantly.
- CNN-F is **robust to inaccuracies** in the measurements.

Conclusions

- **Compact features**, like the dominant eigenvalues of the state matrix, are effective to characterize events and robust to initial conditions.
- The proposed **CNN classifier** trained on single events is able to identify successive events in real time.
- The CNN-F using the dominant features is robust to **the measurement inaccuracies and small training datasets**.
- The proposed **prediction-subtraction** process can reduce the impacts of earlier events and enhance the identification accuracy.

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Reference

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Acknowledgements

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