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A CNN-based Differential Image Processing Approach for Rainfall Classification

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Outline

- Background and Objectives
- Methodology
  - Experimental Setup
  - Differential Image
  - SqueezeNet CNN
- Results and Discussion
- Conclusions

Background and Objectives

- Rainfall monitoring is critical for preventing hydro-geological risks
- Traditional rain monitoring methods
  - local rain gauge: low territorial coverage, insufficient temporal precision, mechanical issue
  - weather radars: better spatial resolution but less accurate estimate, expensive
- This paper propose a low-complexity and cost-effective video rain gauge
- Proposed a new approach to rainfall classification based on image processing and video matching process employing CNN
- Classified the rainfall into 7 levels from “No rain” to “Cloudburst” with average accuracy of 75%

Experimental Setup

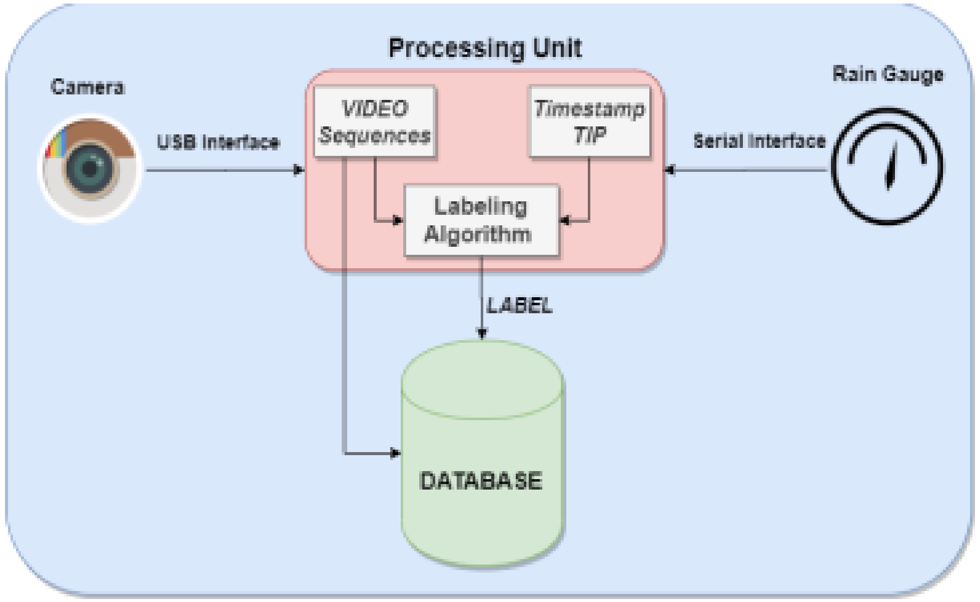

Figure 1: Block Scheme of Video Acquisition System

Table 1. Rain classification and precipitation intensity range.

Rain Classification	Precipitation Intensity
No rain	<0.5 mm/h
Weak rain	0.5–2 mm/h
Moderate rain	2–6 mm/h
Heavy rain	6–10 mm/h
Very heavy rain	10–18 mm/h
Shower	18–30 mm/h
Cloudburst	>30 mm/h

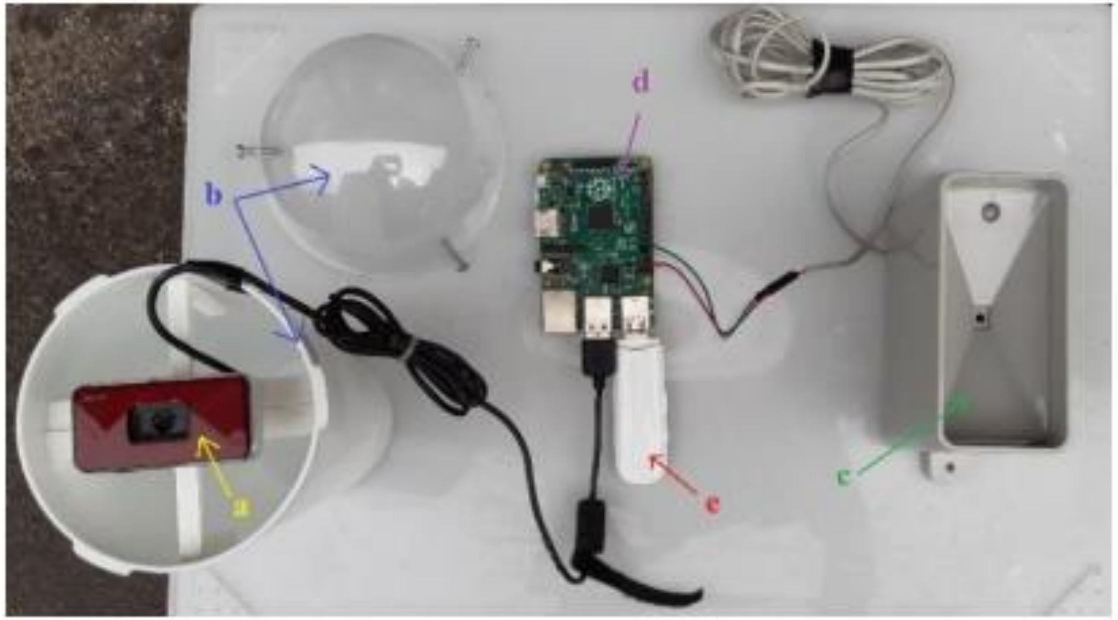

Figure 2: Hardware Components of the Acquisition System

- Camera (a);
- Plastic shaker with a transparent cover (b);
- Tipping bucket rain gauge (c);
- Raspberry Pi (d);
- 4G dongle (e).

Imaging Processing

- Matrix representation of differential images

$$f_{ij}^{d} = f_{ij}^{2} - f_{ij}^{1} =$$

$$= \begin{pmatrix} f_{00}^{2} & \cdots & f_{0N}^{2} \\ \vdots & \ddots & \vdots \\ f_{M0}^{2} & \cdots & f_{MN}^{2} \end{pmatrix} - \begin{pmatrix} f_{00}^{1} & \cdots 0 & f_{0N}^{1} \\ \vdots & \ddots & \vdots \\ f_{M0}^{1} & \cdots & f_{MN}^{1} \end{pmatrix} =$$

$$= \begin{pmatrix} f_{00}^{d} & \cdots & f_{0N}^{d} \\ \vdots & \ddots & \vdots \\ f_{M0}^{d} & \cdots & f_{MN}^{d} \end{pmatrix}.$$

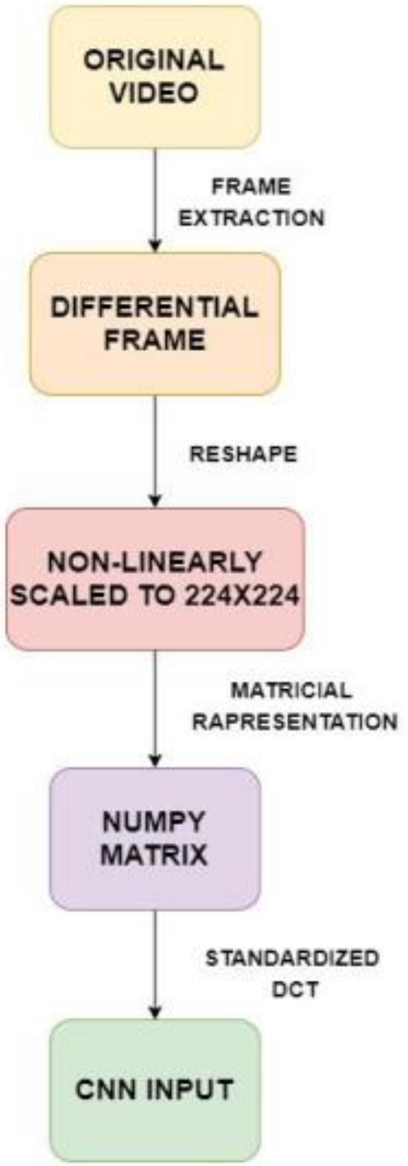

Figure 6: Image Processing Flowchart

Analysis on Differential Images

- Average error: indicates the difference between the two images in terms of RGB scale value;
- Standard deviation: indicates how much the second image varies compared to the first;
- Total of error pixels: indicates the total amount of different pixels between the first image and the second image (from which the "differential image" is obtained).

Table 2: Standard Deviation for Each Precipitation Intensity

Rain Classification	Standard Deviation						AVG
No rain	2.0	2.0	2.0	2.1	2.1	2.0	2.0
Weak	3.6	3.3	2.8	2.4	2.7	2.5	3.0
Moderate	3.3	3.3	4.0	5.7	4.5	5.3	4.4
Heavy	3.4	8.6	5.2	5.3	7.8	5.7	5.8
Very heavy	6.2	5.1	4.1	8.4	6	5.4	6.3
Shower	4.0	8.3	9.6	10.0	8.2	9.3	8.1
Cloudburst	17.3	7.4	10.7	15.4	8.5	11.4	11.9

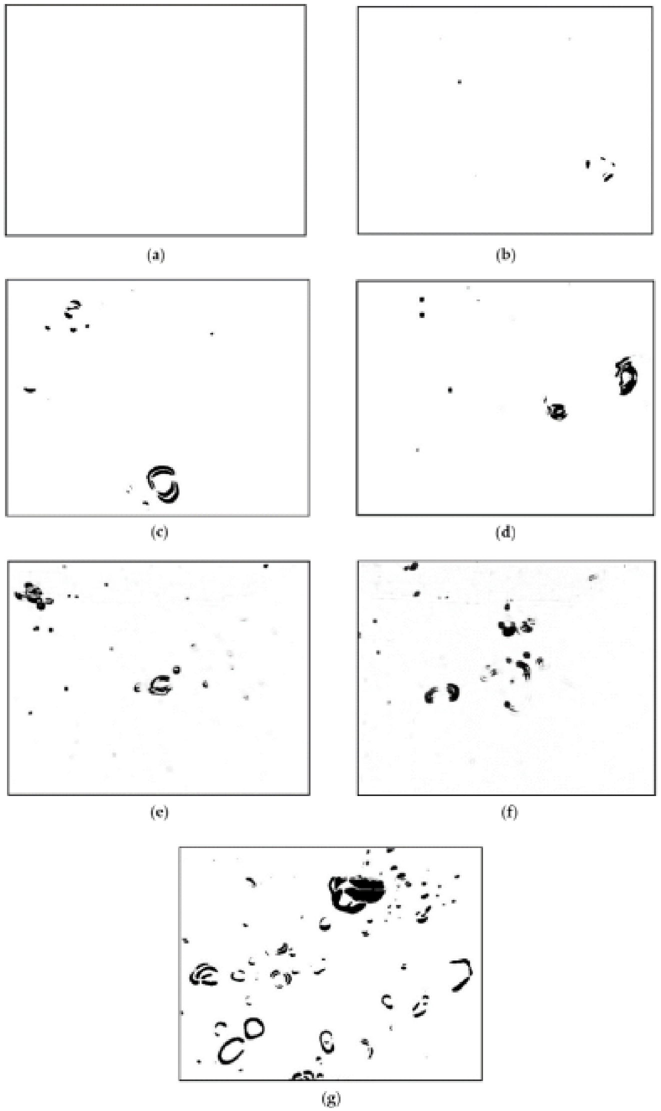

Figure 4: Examples of "Differential Image" for Each Level of Intensity

SqueezeNet CNN

- 2 convolutional layers with 8 fire modules
- Increasing # of filters in the fire modules
- Alexnet-Level accuracy with 50x fewer parameters and <0.5mb model size (Iandola, 2016)

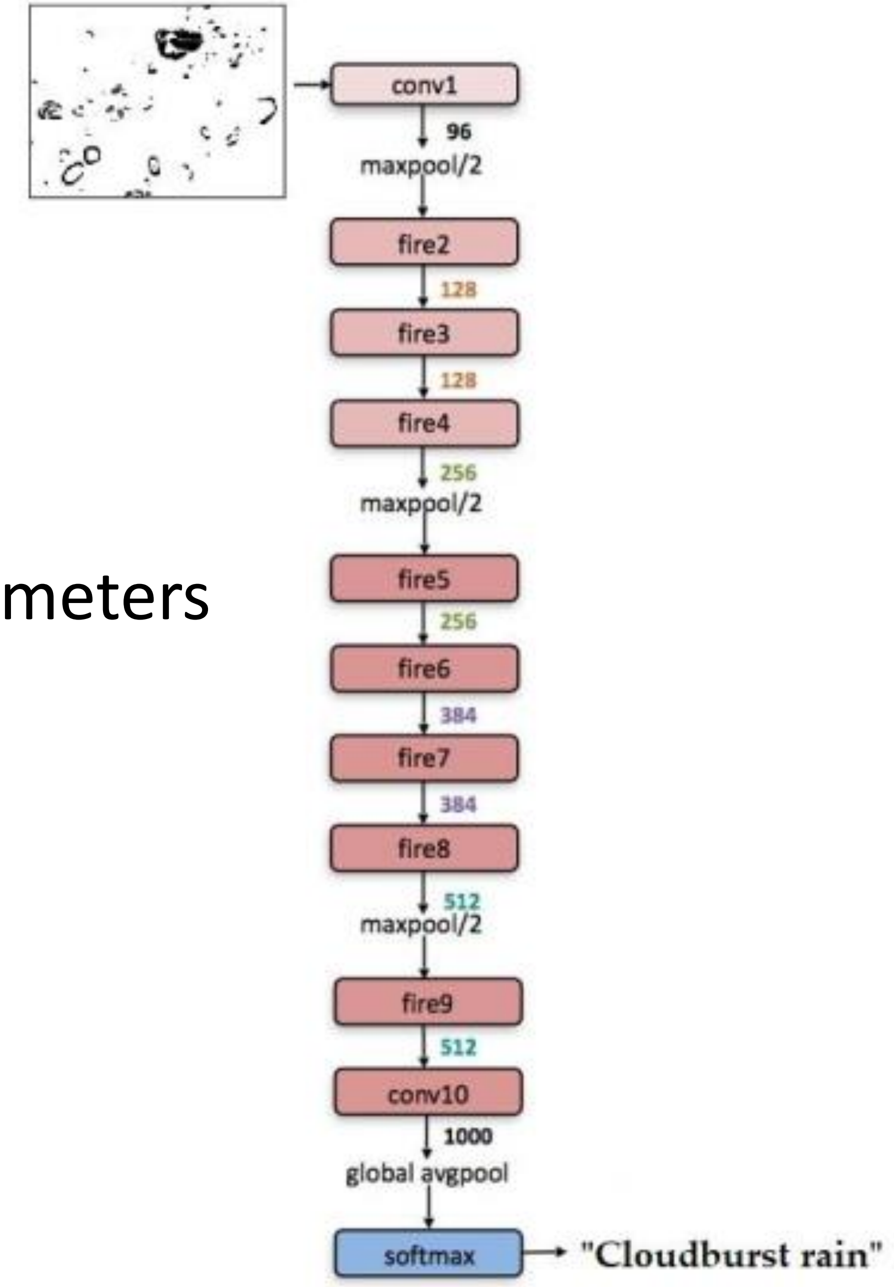

Figure 5: SqueezeNet Architecture

Results

- average classification accuracy is 49%
- reach 75% if considering adjacent miss-classification

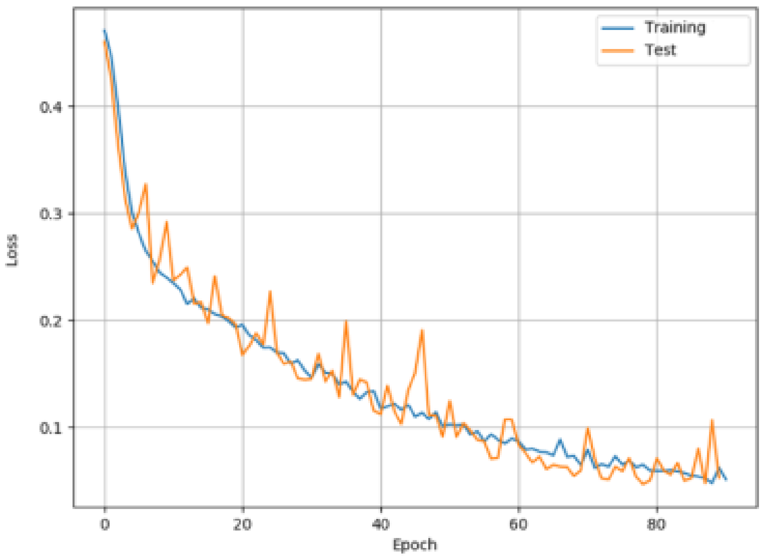

Figure 7: Training and Test Losses with Sub-block 16×16

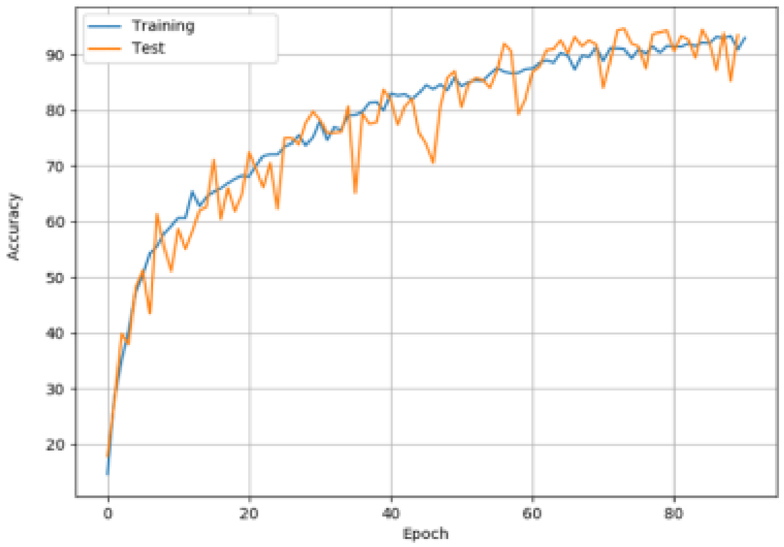

Figure 8: Training and Test Accuracy with Sub-block 16×16

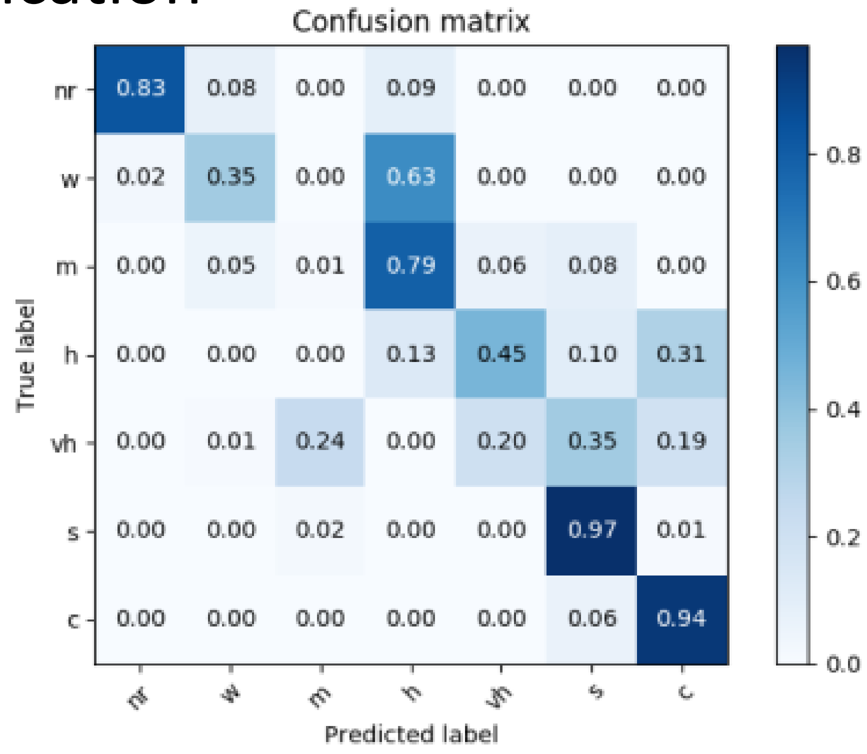

Figure 9: Confusion Matrix with Sub-block 16×16

Conclusions

- Provided an alternative to traditional rain gauges which is based on the extraction of differential frames from video sequences
- Low-complexity and cost-effective system
- Classified rain intensity level into 7 classes with up to 75% accuracy
- Drawback: images used are facing towards the sky, simplified problem

Back Up