Disaster Images Classification using Principal Component Analysis and Neural Networks

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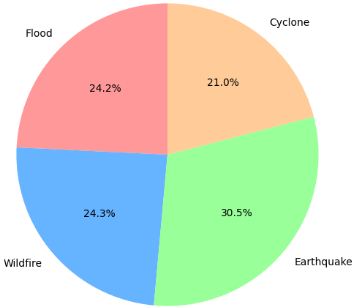
Overview

Introduction

- Disaster management and response require efficient and timely identification of different disaster events.
- With the increasing availability of image data, automated image classification systems have gained significant attention for disaster management applications.

Dataset

- The disaster image dataset was acquired from Kaggle and constists of 4428 images :
  - Earthquake: 1350 images
  - Wildfire: 1077 images
  - Flood: 1073 images
  - Cyclone: 928 images

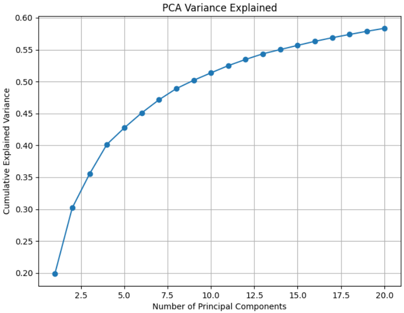


Experiment 1: PCA and Image Classification

- In this experiment, Principal Component Analysis (PCA) was employed as a dimensionality reduction technique to preprocess the image data before classification
- The resulting **k** eigenvectors represent the new basis in which the data can be projected onto a lower-dimensional space.

How to find the k that best describes the dataset ?

- Solution : Explained variance plot (right).
- $\mathbf{k = 20}$



Experiment 1: PCA and Image Classification

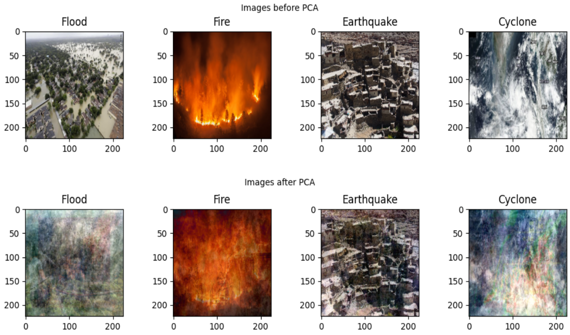


Figure: Example disaster images from each class, before and after PCA. After PCA procedure, images are fitted into an SVM and Random Forest model.

Experiment 2: Custom CNN

- In this experiment, a custom Convolutional Neural Network (CNN) model was trained for disaster image classification.
- The CNN model architecture (right image) consists of multiple convolutional and pooling layers followed by fully connected layers.

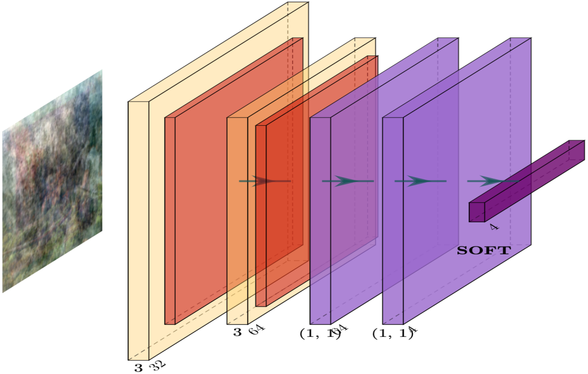


Figure: myCNN model architecture.

Experiment 3: Transfer Learning

- In this experiment, transfer learning was employed to leverage a pretrained MobileV2-Net model for disaster image classification.
- Transfer learning involves using the knowledge learned from a large-scale dataset to fine-tune the model on a smaller target dataset.
- The MobileV2-Net model, pre-trained on a large dataset, was fine-tuned using the disaster image dataset to achieve better performance.

Figure: Performance of pre-trained MobileV2-Net model, finetuned to our disaster image dataset.

Results

Algorithm	accuracy	f1-score
PCA + SVM	0.7	0.7
PCA + Random Forest	0.7	0.7
myCNN	0.60	0.61
MobileNet v2	0.94	0.94

Table: Final Evaluation

Results and Conclusion

The results of the three experiments were as follows:

- Experiment 1 (PCA and Image Classification): The accuracy and F1-score achieved by PCA combined with SVM and Random Forest models were approximately 0.7, indicating neutral results.
- Experiment 2 (Custom CNN): The custom CNN model achieved an accuracy and F1-score of approximately 0.61, suggesting limited performance.
- Experiment 3 (Transfer Learning): The transfer learning approach using the MobileV2-Net model achieved an accuracy and F1-score of 0.94, demonstrating its effectiveness in accurately classifying the disaster images.

In conclusion, the transfer learning approach outperformed the other two methods, showcasing the potential of leveraging pre-trained models for image classification tasks with limited data.

The End

Thank you!