Machine Learning Framework for In-Disaster People Detection

문 우 영

moon.wooyoung@gmail.com

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Response Letter

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1. 심사 의견 개요 (1)

• 1차 심사 개요

- 논문제목 : Machine Learning Framework In-Disaster People Detection
- 심사일시 : 2018년 10월 1일 18:00

• 1차 심사의견

번호	심사 의견	심사 위원	심사의견 상세	논문 페이지
1	초기 파라미터 설정 및 weight에 대한 기술이 필요함	이정진 교수님	• 재난 상황의 훈련 및 모델이 개선된 데이터가 필요함. 이에 따라 training 단계의 초기 Parameter를 설정하고 훈련 하면서 weight를 주어 정확도록 높이는 내용을 기술할 필요가 있음	
2	기존연구와 차별화 되는 전략 목표가 추가되어야 함	최광선 박사님	• 3장 앞에 기존연구와 차별화 되는 전략의 기술이 필요함. 전략 목표 및 구성이 보이지 않음	

1. 심사 의견 개요 (2)

• 1차 심사의견

번호	심사 의견	심사 위원	심사의견 상세	논문 페이지
3	재난 식별을 위한 구체적 예시 및 결과 수준을 예측할 수 있어야 함	최광선 박사님	• 실제 활용할 application에 대한 기능성이 필요함 • 구체적 예시가 필요함. • 결과 수준의 예측이 가능 해야함	
4	파라미터 설정의 최적화가 필요함	최광선 박사님	• Blur한 이미지를 clear한 이미지로 학습하기 위해서는 모델 Parameter 의 최적화가 필요함	
5	Process for detecting disaster 에 detail 한 설명 필요	이재유 교수님	• 뒷부분에 상세한 내용이 기술이 되어 있지만 P31페이지의 설명에 detail 한 설명의 추가가 필요함	
6	재난상황의 People Detection accuracy를 높이는 방안이 필요함	이재유 교수님	• 재난상황에서는 people의 상태가 서있을 경우, 누워있는 경우 다양한 사례가 있음. 이를 발견하기는 매우 어려운 문제가 될 수 있음. 정확도를 높이는 방안이 필요함	

1. 심사 의견 개요 (3)

• 1차 심사의견

번호	심사 의견	심사 위원	심사의견 상세	논문 페이지
7	Time Efficiency의 Total Time은 detection까지 조정 권고함	이재유 교수님	• P55에 기술된 time efficiency는 이벤트를 전달하고 해결하는 범위는 제외하고 detection 하는 부분까지 하는 것이 좋을 것 같음.	

의견 1에 대한 반영내용

의견	재난 상황의 훈련, 모델 개선된 데이터 기술이 필요함. Training 단계 초기 Parameter를 설정, 훈련 시 파라미터 튜닝을 통한 파라미터의 정확도를 높이는 절차를 기술할 필요가 있음	심사위원	이정진 교수님

반영내용

심사의견에 따라 7.2 experiment에 재난 및 People Detection을 위한 training data set, 초기 parameter, 튜닝 이후의 parameter와 training 단계에 대한 구체적 사례 및 절차를 제시하였습니다.

→ '7.2' experiment : 모델 Training 을 위한 재난과 People training data, parameter 튜닝 방법을 제시함.

의견 2에 대한 반영내용

의견	3장 앞에 기존연구와 차별화 되는 전략의 기술이 필요함. 전략 목표 및 구성이 보이지 않음	심사위원	최광선 박사님

반영내용

심사의견에 따라 논문의 1.Introduction에 기존연구와 차별화 되는 전략의 기술 및 실험 목표를 제시하고 연구의 차별화 특징을 제시하였습니다

→ 1.1 Motivation : 실험 목표를 통한 차별화 전략 제시

의견 3에 대한 반영내용

의견	재난 식별을 위한 구체적 예시, 결과 수준을 예측할 수 있어야 함 실제 활용할 application에 대한 기능성 제시가 필요함 구체적 예시가 필요함.	심사위원	최광선 박사님

반영내용

심사의견에 따라 선택한 알고리즘 및 모델의 품질을 예측하는 과정을 design 단계에 추가함으로 결과수준을 예측할 수 있도록 하였으며, experiment 단계에 재난 식별의 구체적 사례를 제시하였습니다.

또한,

→ 5.1 & 5.2 Detail Design : 알고리즘 및 모델의 품질을 예측하는 과정을 추가

→ 7.2 experiment : Training 된 모델을 통한 재난 식별의 구체적 사례 및 성능 제시

의견 4에 대한 반영내용

의견	Blur한 이미지를 clear한 이미지로 학습하기 위해서는 모델 Parameter 의 최적화가 필요함	심사위원	최광선 박사님

반영내용

심사의견에 따라 design 단계에 모델 Parameter의 최적화 단계를 기술하였으며 experiment 단계에 재난 및 People Detection을 위한 Parameter가 최적화되는 구체적 내용을 제시함

→ 5.1 & 5.2 Detail Design : 모델 파라미터의 튜닝 과정을 추가

→ 7.2 experiment : 모델 Training 사례에서 Parameter 최적화 단계 기술 , 모델 Training 및 튜닝의 구체적 사례 제시

의견 5에 대한 반영내용

의견	뒷부분에 상세한 내용이 기술이 되어 있지만 P31페이지의 설명에 detail 한 설명의 추가가 필요함	심사위원	이재유 교수님

반영내용

심사의견에 따라 5.1 Process for detecting disaster에 detail 한 설명을 추가함

→ 5.1 Design for detecting disaster : 개념 설명 시 detail 한 설명을 추가함으로 이어질 내용에 대한 이해를 높일 수 있도록 하였음

의견 6에 대한 반영내용

의견	재난상황에서는 people의 상태가 서있을 경우, 누워있는 경우 다양한 사례가 있음. 이를 발견하기는 매우 어려운 문제가 될 수 있음. 정확도를 높이는 방안이 필요함	심사위원	이재유 교수님

반영내용

심사의견에 따라 6. Design for Quality requirement에 people detection accuracy를 높이는 방안을 추가함

→ 6 Design for quality accuracy: accuracy가 높아질 수 있도록 방안을 제시함

의견 7에 대한 반영내용

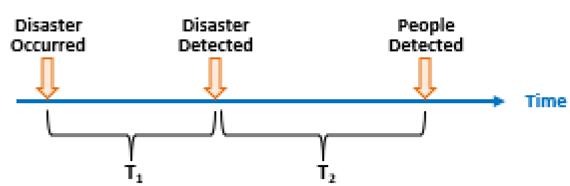
의견	P55에 기술된 time efficiency는 이벤트를 전달하고 해결하는 범위는 제외하고 detection 하는 부분까지 하는 것이 좋을 것 같음.	심사위원	이재유 교수님

반영내용

심사의견에 따라 심사의견에 따라 6.2 Design for Time Efficiency의 Total time Tsum에서 T3(People detect to deliver the analytics result's time)을 제거함

→ 6.2 Design for time efficiency: T3 제거

- **Minimize the total time, Tsum**
  - $T_{sum} = T_1 + T_2$



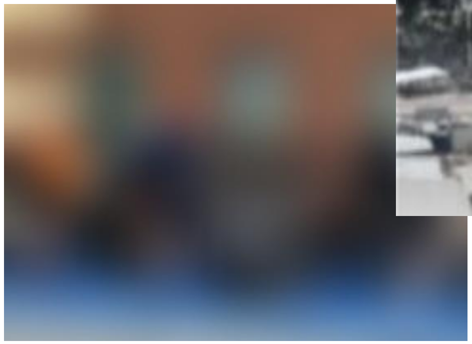
Unit 1.
Motivation & Milestones

Motivation (1)

- **Demands**
  - ***Disaster Occurrence*** **is a serious problem in our society.**
  - **Disasters can create fatal threats to the safety of life.**
  - **Hence, effective handling disaster is essential in keeping our life safe.**
  - **Disaster can effectively be managed by utilizing advanced IT.**
    - Software Framework for Detection of Disaster & People
    - High Accuracy of Detection with Machine Learning

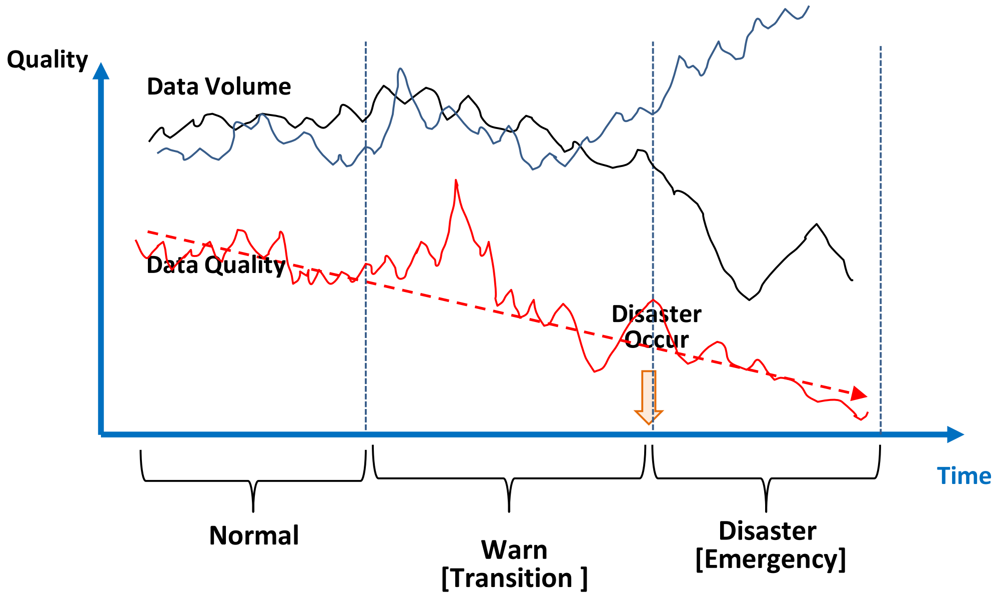
Motivation (2)

- **Technical Hardship**
  - **In disaster situation, the quality of collected camera images and sensor values is considerably low. This is due to;**
    - Heat, Fire, Flame, Smoke, Vibration, utility disconnection, etc.
  - **Detecting people with low-quality measurement becomes hard.**
    - Missing people presence
    - Incorrect Detection



Issues

- **Detection**
  - **Disaster suddenly occur;**
    - Timeliness of disaster detection.
    - After a disaster occurred , it is hard to recognizing the situation because the quality of collected data is poor due to poor environmental quality (disconnection, unclear data)
  - **People presence detection.**
    - the quality of collected data is poor



Solutions

- **Disconnection: Using Previous gathered data**
  - **A Disaster Profile is a tuple of (Disaster Type, List Symptoms, Characteristics)**
    - Disaster Type
      - Type of the Disaster
    - Symptom
      - Observable State of the Environment such as Temperate, Object Shifting, Noise, etc.
      - Tuple of (Symptom Attribute, Value Range, Annotation)
    - Characteristics
      - Additional Description of the Disaster
  - **Statistical analytics and ML Model generation.**
- **Poor Quality : Purify**
  - **Generate a clear high-resolution people from a blurry small one**

Research Milestones

- **Milestones**
  - **Design of Detecting <u>Occurrences</u> of Disaster**
  - **Design of Detecting <u>Presence of People</u> in Disaster**
- **Quality Goal**
  - **High Accuracy**
  - **Time Efficiency**

Unit 2.
State-of-the-Art Survey

- Works on Disaster Detection
- Works on People Detection

Works on Disaster Detection (1)

- **[Fuentes et al., 2018]**
  - **Laura Lopez-Fuentes et al., Review on Computer Vision Techniques in Emergency Situation, 2017 *Multimedia Tools and Applications (pp. 1-39)***
    - distinguish two generic emergency groups: natural emergencies and man-made emergencies.
    - Natural emergencies are divided into three emergency types: fire, flood and drought.
    - Emergencies caused by humans are divided into two subtypes depending on the scope: emergencies that cause dangers to multiple persons and emergencies that cause dangers to a single person.

Generic Emergency Group	Emergency sub-group	Emergency Type
Natural emergencies		Fire Flood Drought Earthquake Hurricane/Tornado Landslide/Avalanche
Man-made emergencies	Single person	Falling person Drowning Injured civilians
	Multiple person	Road accident Crowd related Weapon threaten

Works on Disaster Detection (2)

- **[Schnizler et al., 2014]**
  - **Francois Schnizler et al., Heterogeneous Stream Processing for Disaster Detection and Alarming, *2014 IEEE International Conference on Big Data (pp. 914-923)***
  - **Method for Disaster Detection**
    - Each incident is characterized by
      - a location, the area affected by the incident
      - a time interval (potentially of length zero) when the event occurred
    - Incidents : Each incident is part of a situation, accident or more complex disaster situation.

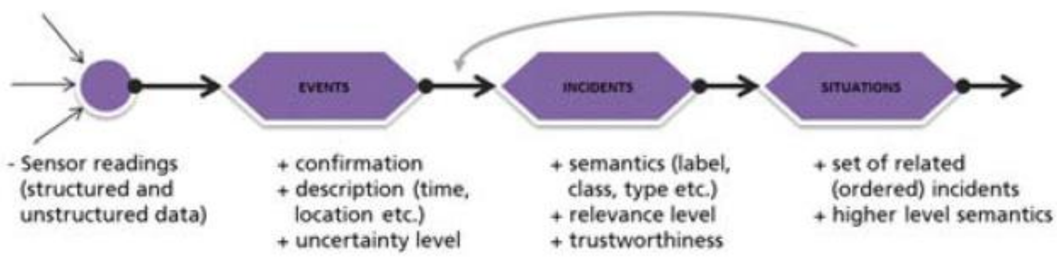


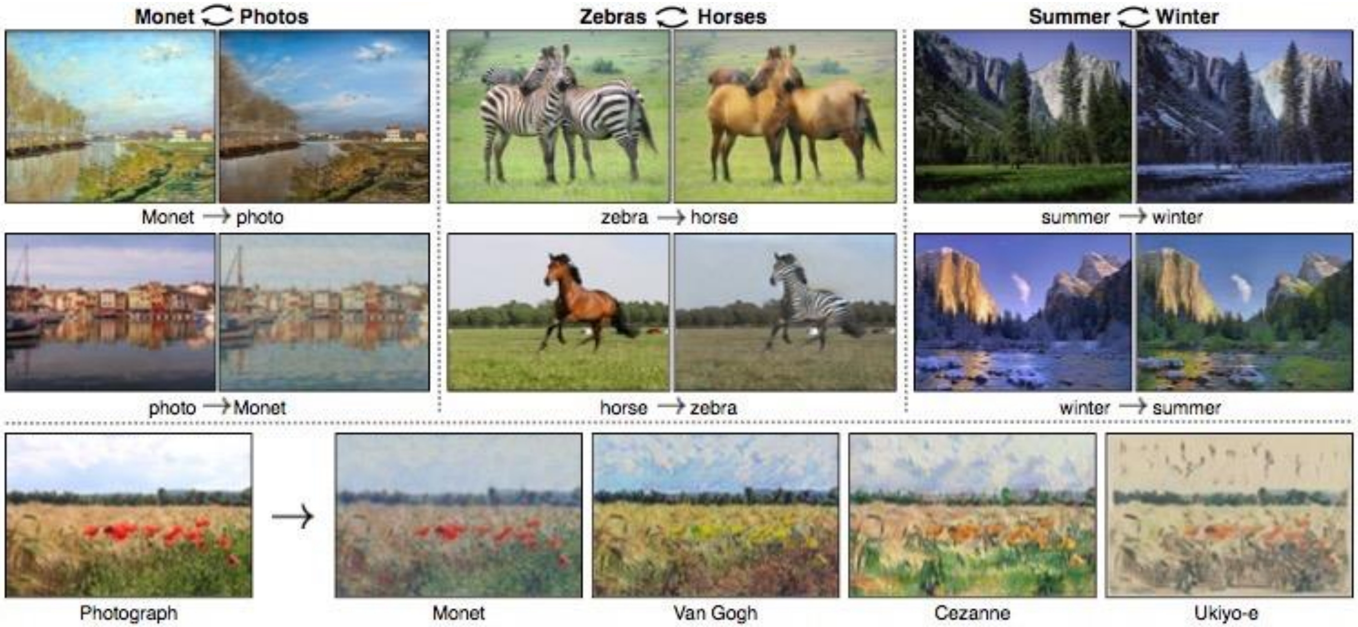
Figure 1: Steps in situation reconstruction

Works on Disaster Detection (3)

- **[Stange et al., 2015]**
  - **Hendrik Stange et al., Insight-driven Crisis Information Preparing for the Unexpected using Big Data, *In 2015 ISCRAM(Information Systems for Crisis Response and Management)***
  - **Feature for Disaster Detection**
    - Fire
      - Flame height, angle, width, smoke, color of fire
    - Water
      - color, ripple pattern of water

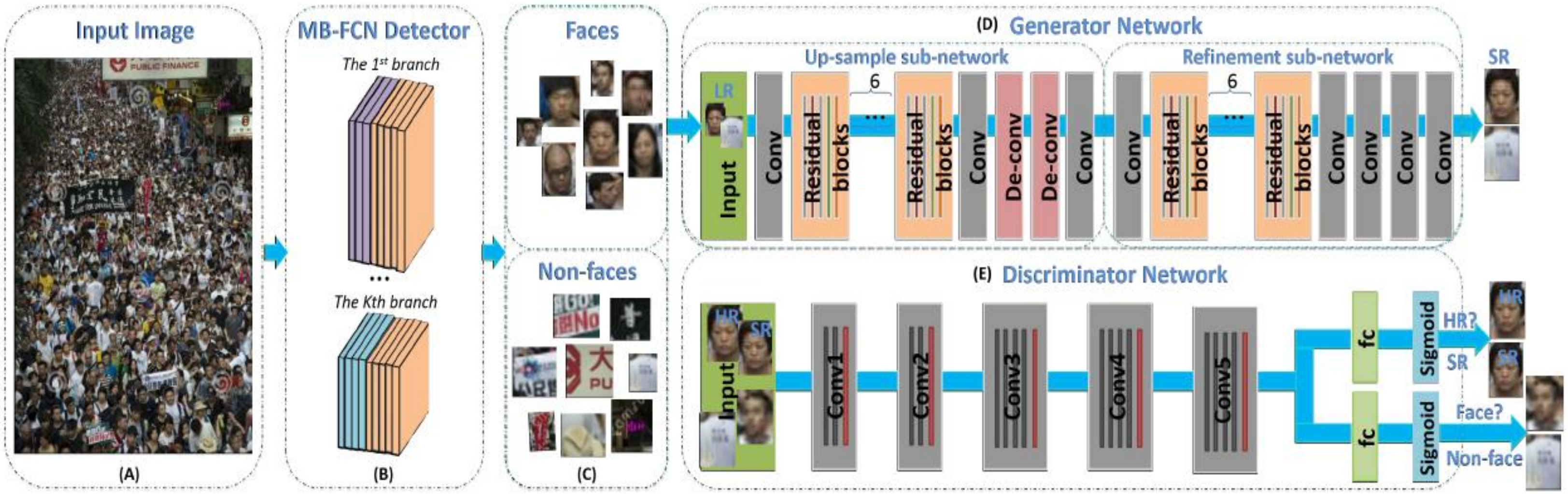
Works on Disaster Detection (4)

- [Zhu et al., 2017]
  - Zhu, Jun-Yan, et al. "Unpaired image-to-image translation using cycle-consistent adversarial networks." arXiv preprint (2017).
  - Given two image collections
    - algorithm learns to translate an image from one collection to the other
    - does not require correspondence between images



Works on People Detection (1)

- **[Bai et al., 2018]**
  - Yancheng Bai et al., Finding Tiny Faces in the Wild with Generative Adversarial Network, 2018 Conference on Computer Vision and Pattern Recognition, IEEE
  - Tiny faces are often lacking detailed information and blurring
  - Generate a clear high-resolution face from a blurry small one by adopting a generative adversarial network



Works on People Detection (2)

- **Elaborating the Figure**

(A) The images are fed into the network;

(B) MB-FCN detector is baseline, it crops the positive data (i.e. faces) and negative data (i.e. non-faces) from the input images for training the generator network and the discriminator network, or generates the regions of interest (ROIs) for testing.

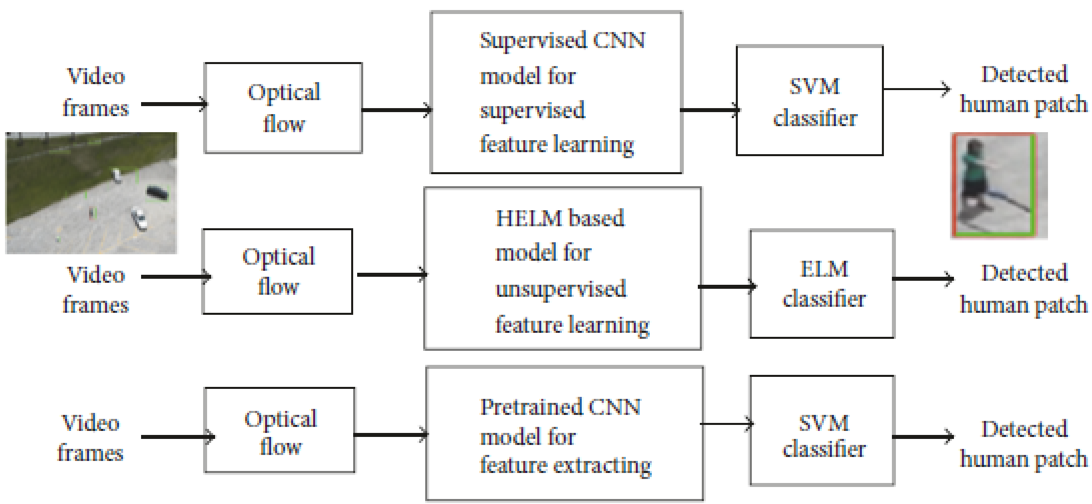
(C) The positive data and negative data (or ROIs) are generated by the MB-FCN detector.

(D) The generator network is trained to reconstruct a clear super-resolution image (4× upscaling) from the low-resolution input image, which includes the up sample sub-network and the refinement sub-network.

(E) The discriminator network is two parallel fc layers, and the first fc layer is to distinguish the natural real images or the generated super-resolution images and the second one is to classify faces or non-faces.

Works on People Detection (3)

- [AlDahoul et al., 2018]
  - Nouar AlDahoul et al., Real-Time Human Detection for Aerial Captured Video Sequences via Deep Models, 2018 Computational Intelligence and Neuroscience
  - Highly abstract and discriminative features can be produced automatically without the need of expert knowledge
  - Automatic feature learning methods which combine optical flow and three different deep models



Works on People Detection (4)

- **Stewart's Work** [Stewart '16]
  - To detect people from images by using a combination of convolutional neural networks (CNN) and recurrent neural networks (RNN)
  - To detect partially occluded instances
- **Lots of other works also propose effective structures of neural networks for people detection.** [Zeng '17][Nguyen '16]...
- **These works focus on increasing accuracy of people detection at building a model.**
  - As characteristics of input data can be changed, accuracy of fixed model would be drop in accuracy.

Works on Machine Learning F/W

- **Baylor's Work** [Baylor '17]
  - To propose a TensorFlow-based machine learning platform which reduces the effort of developing general ML applications
  - To develop reusable components for data analysis, data validation, model training, model evaluation, and serving infrastructure
- **There are many domain-specific machine learning platforms.** [Remita '16][Rahman '17]
  - Genome Classification
  - Biomedical Image Analysis
- **It is needed to serve people detection results with diverse schemes including pulling and pushing.**

Unit 3.
Functionality of Framework

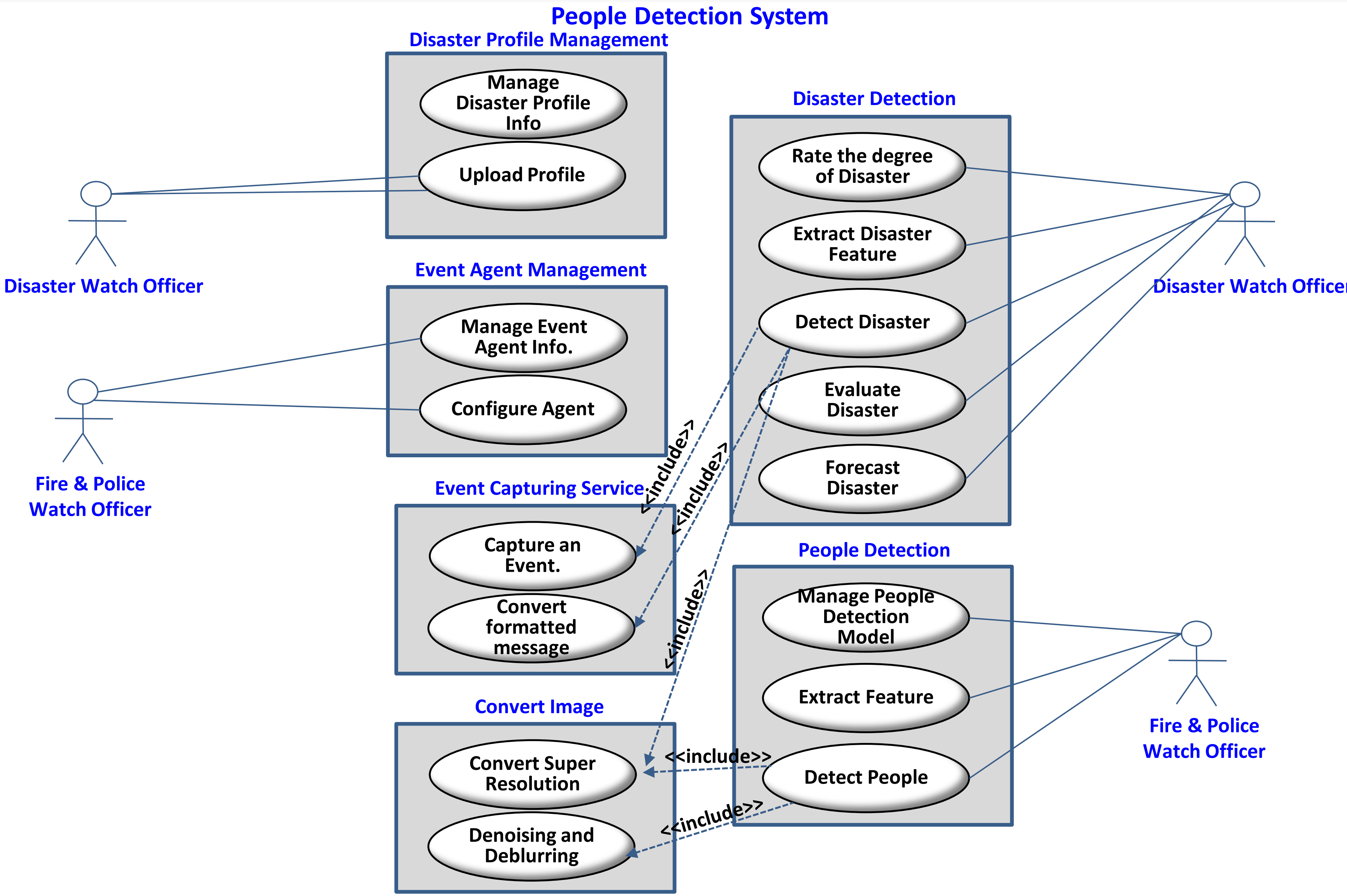
Functional Groups (1)

- **Disaster Profile Management**
  - Overall Disaster profile management for natural and man-made type.
  - Manage disaster type, symptoms, characteristics
- **Event Agent Management**
  - Manage Agent type, location, information
  - Configure Agent for event capturing
- **Event Capturing Service**
  - Capture an events placed in different location on the network
  - Capture an event and information for any changes of contents
  - Convert formatted message

Functional Groups (2)

- **Disaster Detection**
  - **Determine possible disaster based on profile and event**
  - **Analytics the disaster and rate the degree of disaster**
  - **Support information for Low-cost and time-efficient analysis**
- **People Detection**
  - **Determine human detection using Video analysis Network**
- **Image Denoising and Deblurring**
  - **Convert Low-Resolution to Super-Resolution**
  - **Denoise and deblur image**

Use Case



People Detection System
Disaster Profile Management
Manage Disaster Profile Info
Upload Profile
Disaster Watch Officer
Event Agent Management
Manage Event Agent Info.
Configure Agent
Fire & Police Watch Officer
Event Capturing Service
Capture an Event.
Convert formatted message
Convert Image
Convert Super Resolution
Denoising and Deblurring
Disaster Detection
Rate the degree of Disaster
Extract Disaster Feature
Detect Disaster
Evaluate Disaster
Forecast Disaster
Disaster Watch Officer
People Detection
Manage People Detection Model
Extract Feature
Detect People
Fire & Police Watch Officer
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Functional Components (1)

- **Disaster Profile Manager**
  - Manage Profile
  - Create Extra Profile Fields(Heading, Input, Hidden Input, Selects, Time zone etc.)
  - Upload Profile for finding disaster
  - Search and Update Profile

- **Disaster Event Processor**
  - Manage Agent
  - Deploy Agent to Target servers
  - Manage Event Pattern & Hierarchies
  - Event Aggregation and transformation

Functional Components (2)

- **Disaster Detector**
  - **Manage Disaster Model**
  - **Detect Disaster (Identification of Events, Evaluation of Events)**
  - **Predict Disaster**

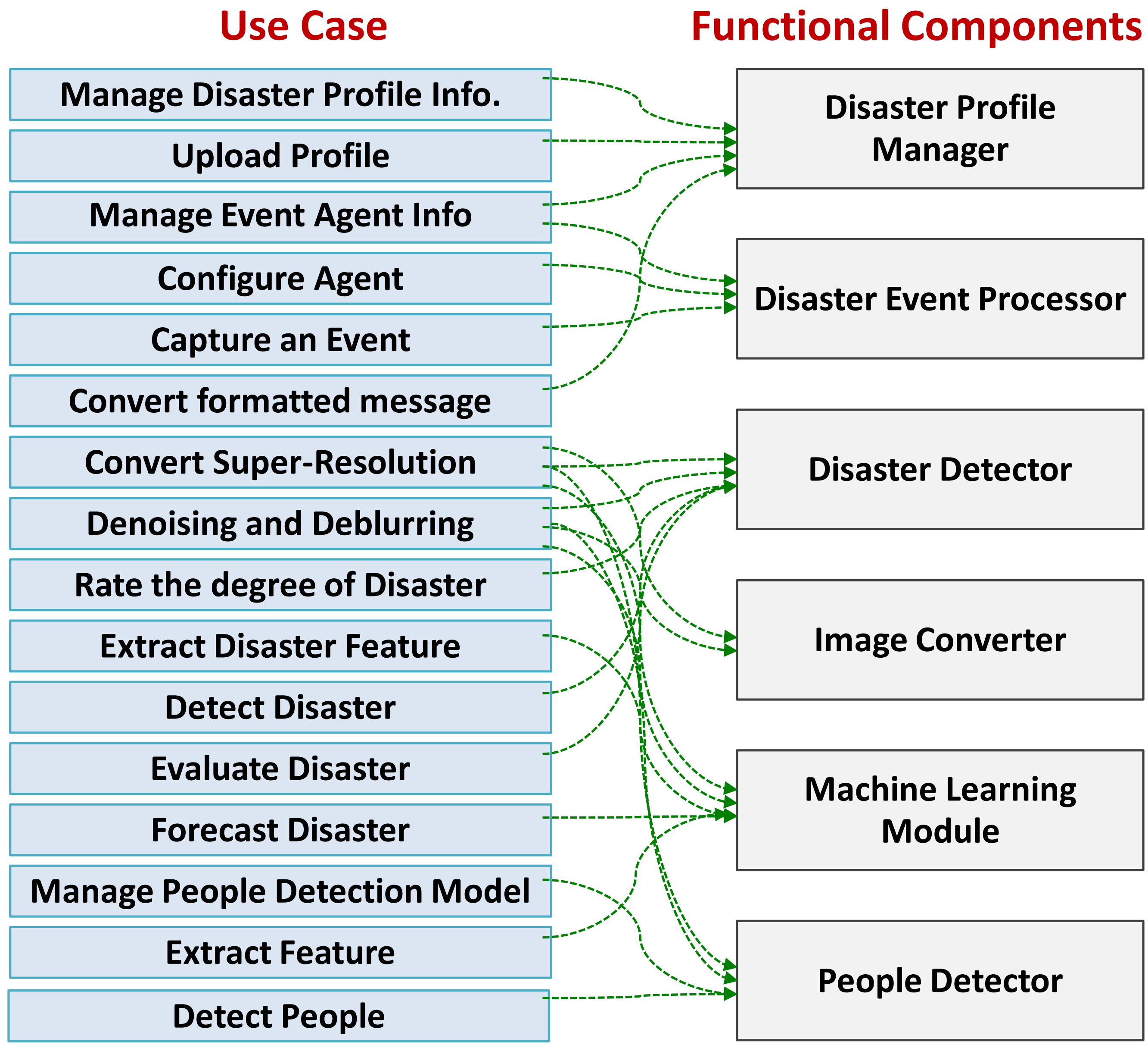
- **People Detector**
  - **Manage People Detection Model**
  - **Detect People**

Functional Components (3)

- **Image Converter**
  - Convert Super Resolution
  - Denoising
  - Deblurring

- **Machine Learning Module**
  - Extract Feature
  - Select Feature
  - Choose Algorithm
  - Training

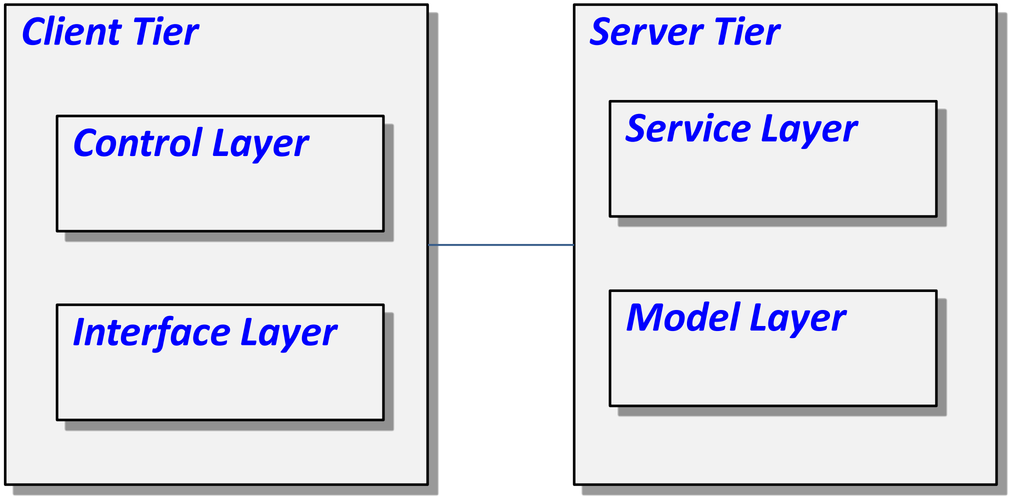
Mapping between 16 Use Cases and 6 Component



Unit 4.
Architecture Design

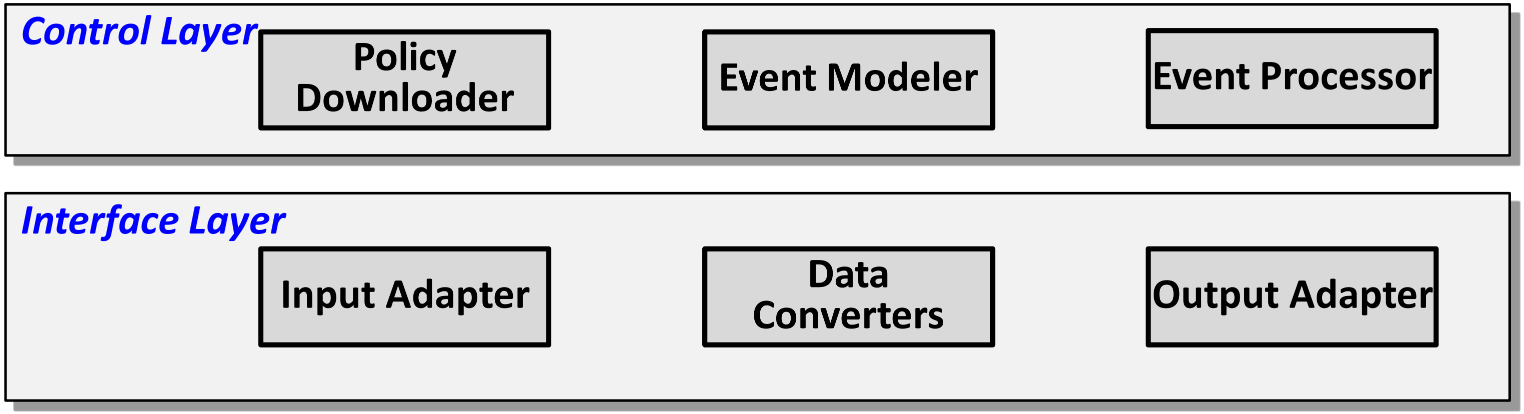
Architecture Styles to Apply

- **Client-Server Architecture Style**
  - **Client**
    - To gather an event and send information for detecting disaster and People
  - **Server**
    - Training Disaster and People detection
    - To store people detection results
- **Layered Architecture Style**
  - **Control Layer**
  - **Interface Layer**
  - **Service Layer**
  - **Model Layer**



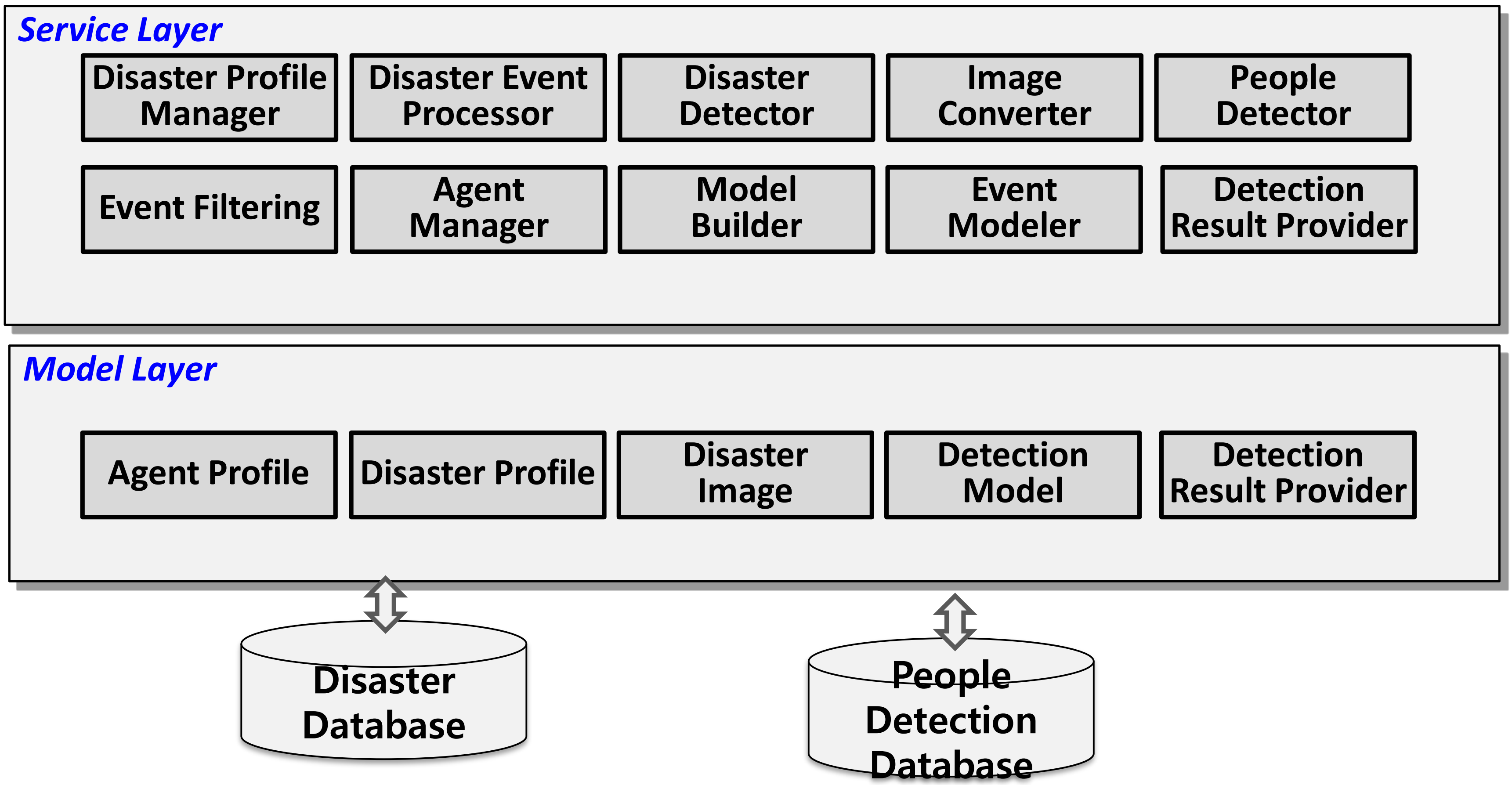
Architecture for Client Tier

- **Client Tier Architecture**
  - **The Client Tier consists of the following components**
    - Input Adapter
    - Policy Downloader
    - Data Converters
    - Event Modeler
    - Event Processor
    - Output Adapter



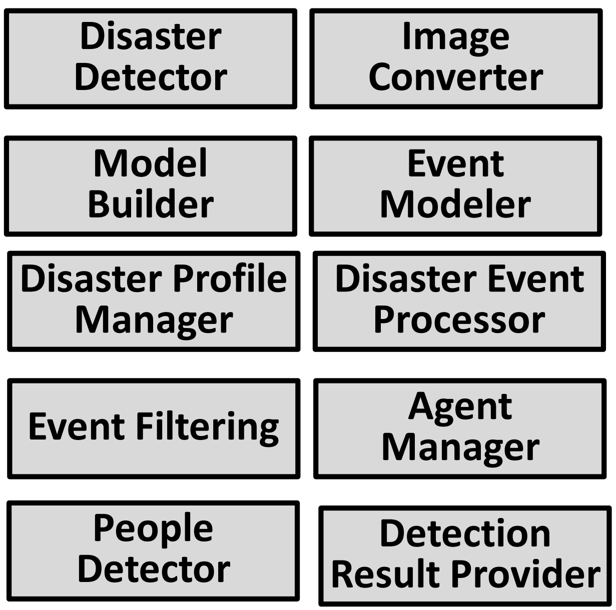
Architecture for Server Tier

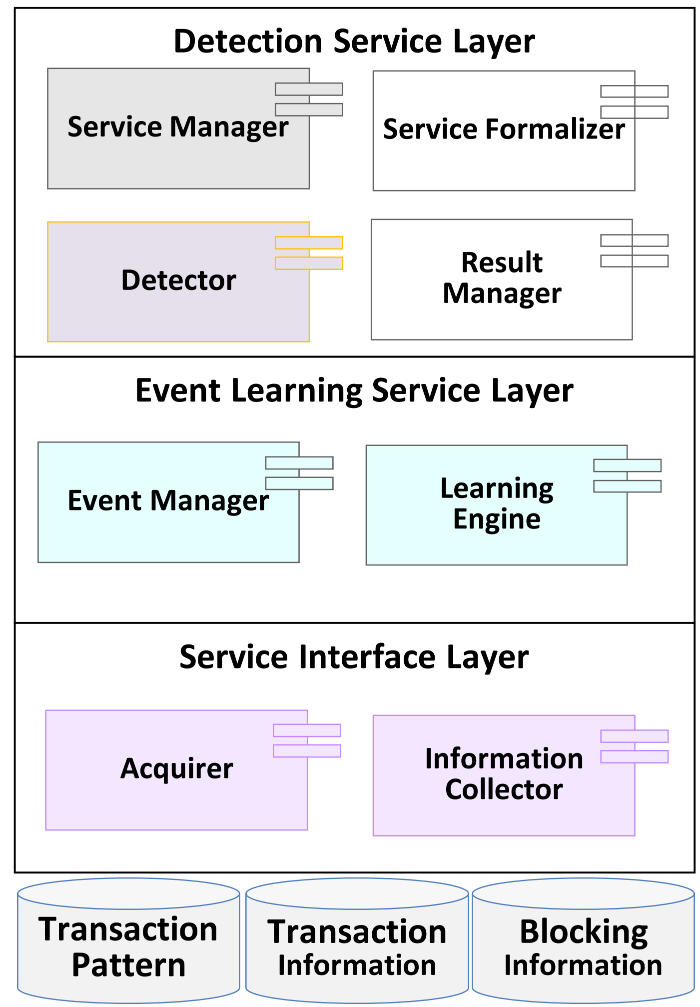
- **Server Tier Architecture**
  - To training Disaster and People detection
  - To store people detection results



Architecture for Server Tier

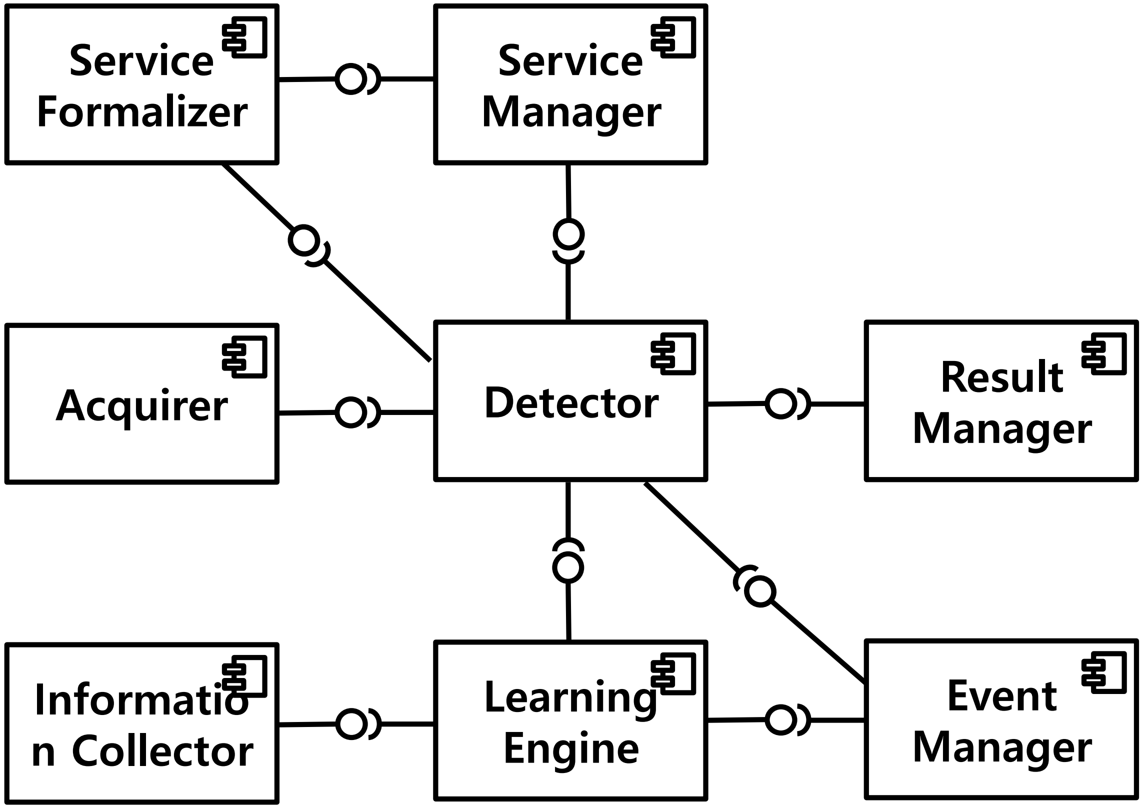
- **Service layer of Framework Architecture**
  - To training Disaster and People detection
  - To store people detection results





Architecture for Server Tier

- View Model of Server Tier Architecture
  - To training Disaster and People detection
  - To store people detection results



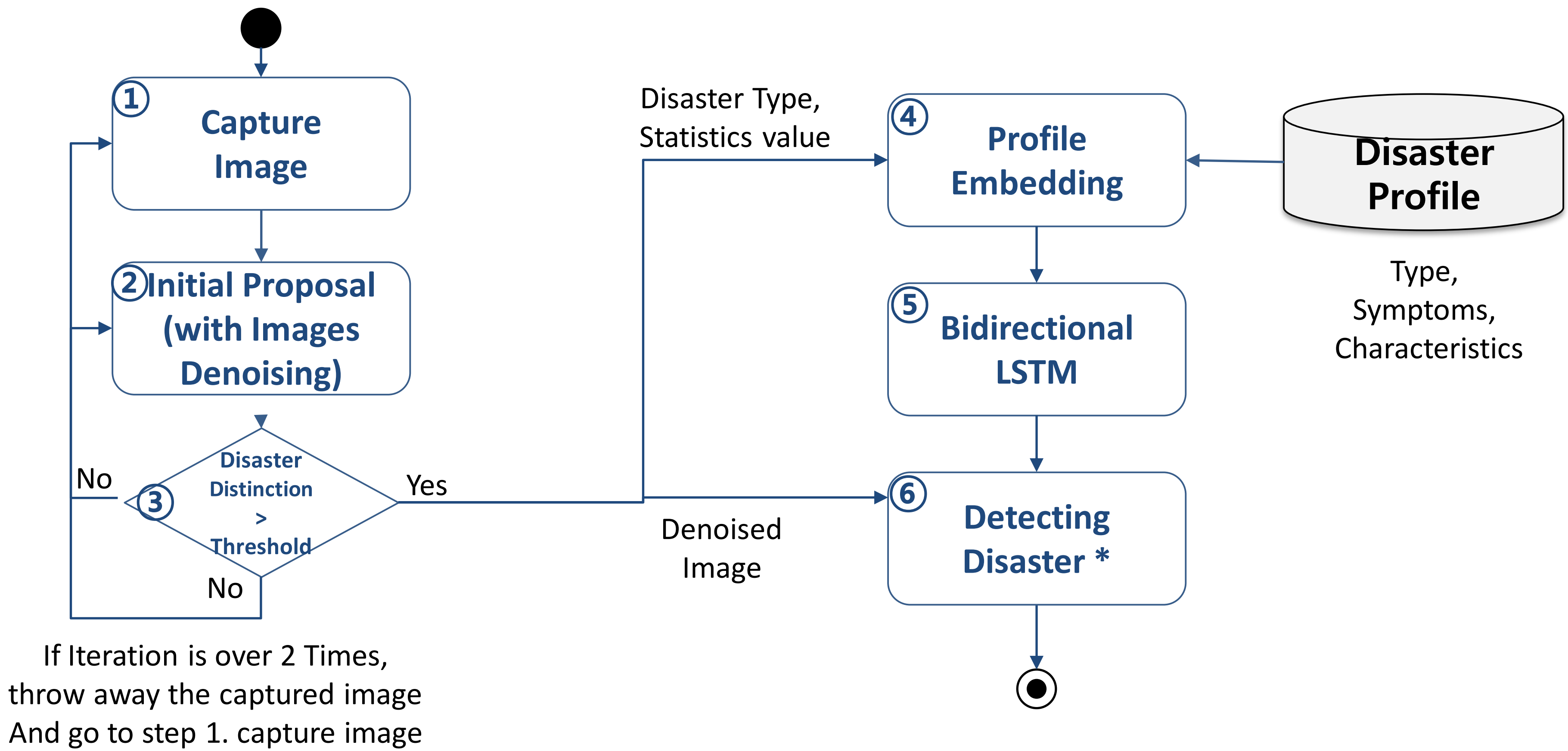
Unit 5.
Detailed Design

- **Design for each Functional Component**

Unit 5.1
Design for Disaster Detection

Process for Detecting Disaster (1)

- **Detecting disaster based on Generator adversarial Network with Disaster Profile**



*** Detecting Disaster : Proposed Disaster Detection algorithm**

Process for Detecting Disaster (2)

- To detect Disaster, our process is
  - Step ① Capture Image Data for Detecting Disaster
  - Step ② Initial Proposal (with Super Resolution, deblurring & denoising)
  - Step ③ Distinction threshold
  - Step ④ Profile Embedding
  - Step ⑤ Bidirectional LSTM
  - Step ⑥ Detecting Disaster

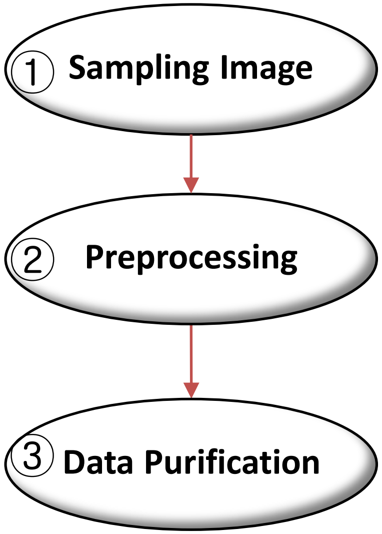
Process for Detecting Disaster (3)

- **To detect disaster on time with high accuracy**
  - **It is hard to determine disaster just blur or single noise image.**
  - **Our approach is based on probabilistic framework and GAN(Generator adversarial Network)[1]**
  - **First) To convert blur or noise image we apply the GAN, using the pre-trained similarity and last decoding model of the network.**
  - **Second) The Disaster Profile contains image and/or metadata, we use a word embedding to represent the textual information[2] in a continuous space and feed it to a bidirectional LSTM[3].**
  - **Finally) We concatenate the image and text features followed by a fully connected layer to give a final probability of the Disaster images**

[1] Goodfellow, Ian, et al. "Generative adversarial nets." Advances in neural information processing systems. 2014.
[2]] Pennington, Jeffrey, Richard Socher, and Christopher Manning. "Glove: Global vectors for word representation." Proceedings of the 2014 conference on empirical methods in natural language processing (EMNLP). 2014.
[3] Yu, Zhou, et al. "Using bidirectional LSTM recurrent neural networks to learn high-level abstractions of sequential features for automated scoring of non-native spontaneous speech." Automatic Speech Recognition and Understanding (ASRU), 2015 IEEE Workshop on. IEEE, 2015.

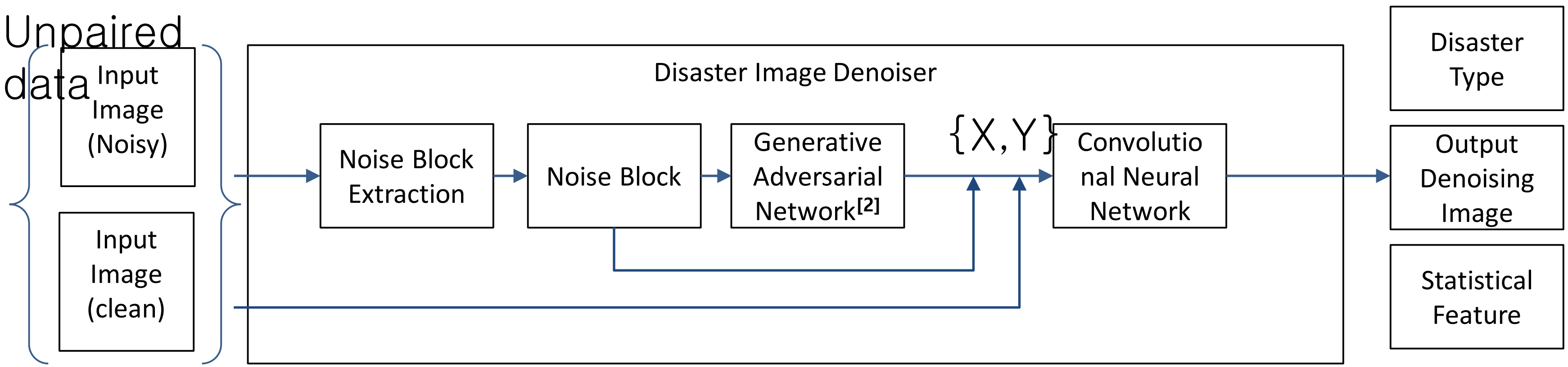
Step ① Capture Image

- **Gather Image Data from agents for Disaster Detection**
  - **Sampling Image data from multiple agents**
  - **Preprocessing the event data :**
    transforming raw data into an pre-defined format.
  - **Data Purification : detecting and correcting (or removing) corrupt or inaccurate record**



Step ② Initial Proposal

- **Initial proposal with Generative Adversarial Network [1]**
  - **Given unpaired data, noise blocks extracted from images are exploited to train a Generative Adversarial Network (GAN)[2]**
  - **Both extracted and generated noise blocks are combined with clean images to obtain paired training data which is used to train a deep Convolutional Neural Network (CNN) for denoising the input noisy images.**
  - **Suggest Disaster Type and provide Statistical Features from denoising image**



[1] Chen, Jingwen, et al. "Image Blind Denoising With Generative Adversarial Network Based Noise Modeling." Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. 2018.
[2] Goodfellow, Ian, et al. "Generative adversarial nets." Advances in neural information processing systems. 2014.

Step ③ Distinction threshold

- **Algorithm of compute Similarity and distinction threshold**

Algorithm 1 Distinction Threshold

Input : threshold

- **Initialization:**
  1) Set similarity $\mathcal{L}_{Similarity}$, $Distinction = 0$;
  2) Set iteration Count = 0;
- **While** not compute **do**
  1) Iteration count ++;
  2) $Distinction =$ Compute $\mathcal{L}_{\mathbf{Similarity}}$;
  3) if *Distinction > threshold* then
     Vector Concatenation;
     else *continue;*

End while

Output : $\mathcal{L}_{Similarity}$

If Iteration is over 2 Times, throw away the captured image And go to step 1. capture image
At the first time, an operator will set the threshold by manually

Step ④ Profile Embedding (1)

• The Disaster Profile Embedding

- **The Disaster Type and Symptoms are initialized using Glove Vector[1], , which we fine-tune with our metadata.**
- **For the metadata we use a disaster embedding to represent the textual information in a continuous space and feed it to a bidirectional LSTM.**
- **Uses ratios of co-occurrence probabilities, rather than the co-occurrence probabilities themselves**

- **The most famous methods to build lower-dimension vector representations for words based on their context**
  - Co-occurrence Matrix with SVD
  - word2vec (Google)
  - ***Global Vector Representations (GloVe) (Stanford)***

[1] Pennington, Jeffrey, Richard Socher, and Christopher Manning. "Glove: Global vectors for word representation." Proceedings of the 2014 conference on empirical methods in natural language processing (EMNLP). 2014.

Step ④ Profile Embedding (2)

- **Represent Disaster**
  - **Fire, Flood, Building Damage due to several causes**

- **Represent disaster-specific 'Symptom'**
  - **Temperature Change**
  - **Color Change**
  - **Object Shifting/Moving**
  - **Noise**
  - **Water Level**
  - **Smog**
  - **Etc.**

- Temporal Feature
  .Background modeling
  .subtraction Temperature
  .Optical Flow
- Convolutional features
- Color feature
- Shape and Texture

- SNS Context
- Utility Disconnect – Electricity
  Water
  Gas..

- Fire *
- Flood *
- Drought
- Earthquake
- Hurricane/Tornado
- Landslide/Avalanche

- Falling person
- Drowning
- Injured civilians
- Road accident
- Crowd related
- Building demolishing*

Step ④ Profile Embedding (3)

- **Disaster Profile**
  - **This profile describes the common symptoms of each disaster type.**
- **Elements of Profile**
  - **The profile is a tuple of three elements;**
    - Disaster Type
    - Set of Symptoms
    - Annotation
  - **A symptom is defined as a tuple of three elements;**
    - Symptom Attribute
    - Value Range
    - Constraints

Step ④ Profile Embedding (3-1)

- **Example) Disaster Profile for Fire**

(Fire, Fire Symptom

{

(pixel fire, (R>G>B) & (|R-B|≥ 90) & (|G-B| ≥40, 1) ,
(pixel fire, (R > 190) & (G > 100) & (B < 180), 1) ,
(color detection , $R_t(x,y) > R_{mean}$, 0)

(CO_2 Resonance, 4.3µm~4.5µm, 2~15H fluctuation)
(smoke size, 10m , under 10km),
(smoke size, 20m ,under 20km)
(fire size Pi , $1m^2$, under 1.8km),
(flame height f_h, $1m^2$, under 1.8km)

}

Trained Image Location)

Step ④ Profile Embedding (3-2)

- **Example *Disaster Symptom Profile*. (Fire)**
- ***(Fire, smoke{(smoke size,10m , under 10km),***
  (smoke size,20m ,under 20km)}, 0)

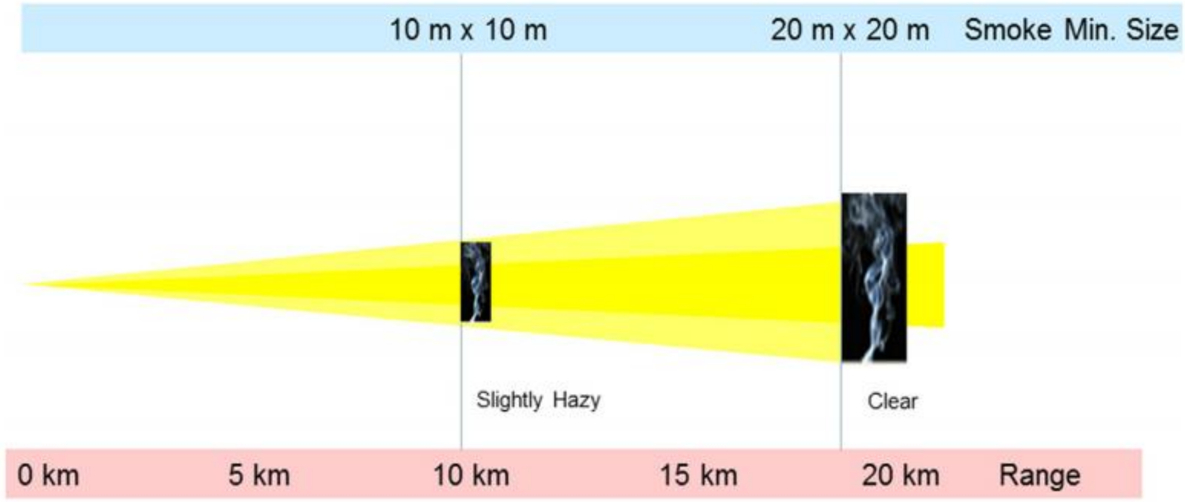


Fig. 12. Minimum smoke size versus detection distance with a visible range camera.

Çetin, A. Enis, et al. "Video fire detection–review." *Digital Signal Processing* 23.6 (2013): 1827-1843.

Step ④ Profile Embedding (3-3)

- **Example *Disaster Symptom Profile*. (Fire)**
- ***(Fire, fire_size{(fire size, P_i 1m^2, under 1.8km),***
  (fire size, P_r 1m^2 ,under 2.7km),
  (fire size, P_d 1m^2 ,under 11km),

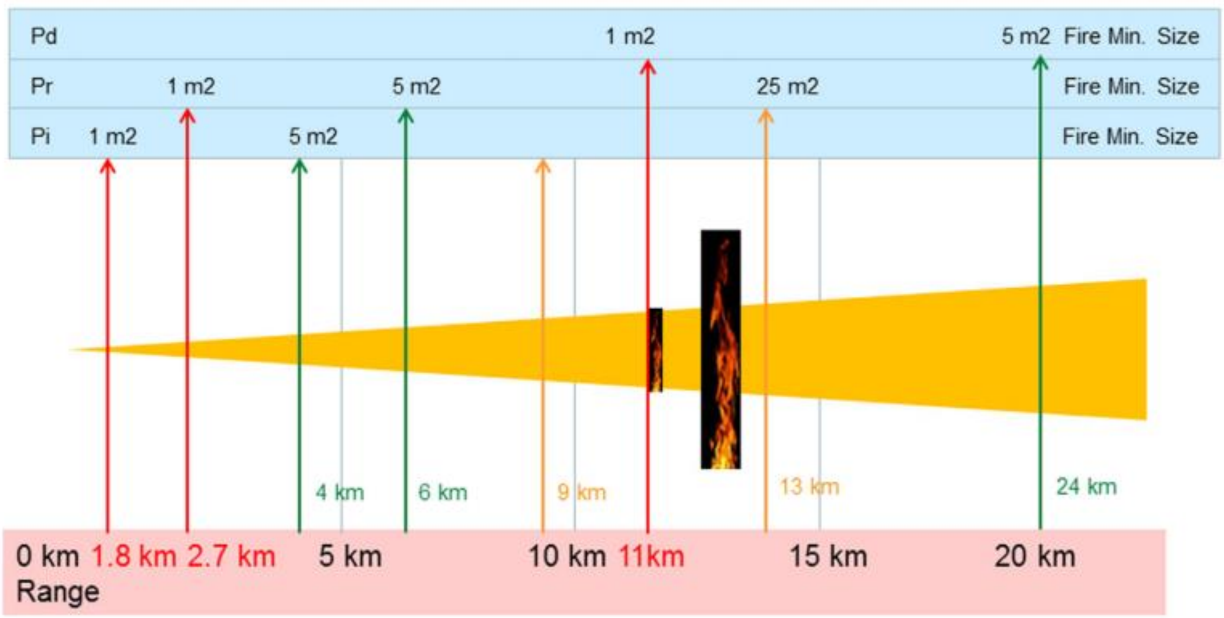
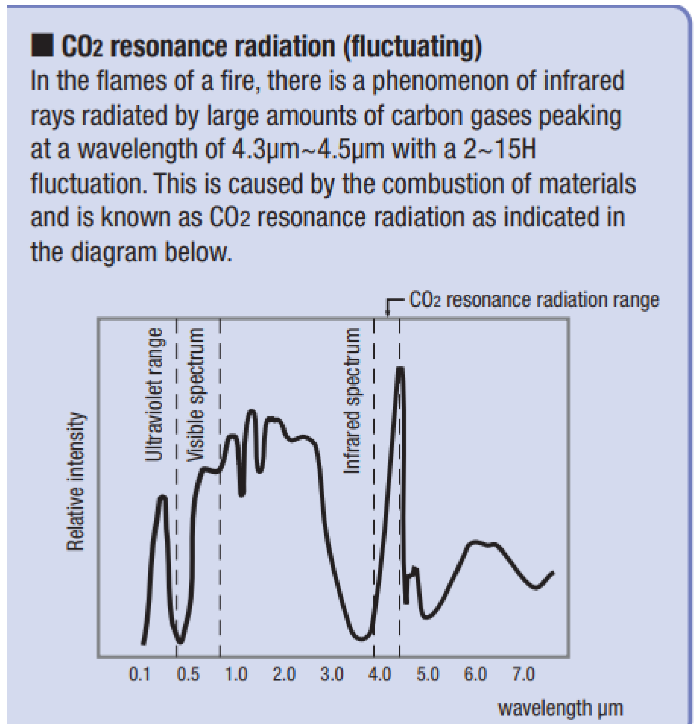


Fig. 14. Minimum fire sizes versus detection, recognition and identification ranges.

Çetin, A. Enis, et al. "Video fire detection–review." *Digital Signal Processing* 23.6 (2013): 1827-1843.

Step ④ Profile Embedding (3-4)

- **Example *Disaster Symptom Profile*. (Fire)**
- ***(Fire, {(CO_2 Resonance, 4.3µm~4.5µm, 2~15H fluctuation), 0)***


CO_2 resonance radiation (fluctuating)

In the flames of a fire, there is a phenomenon of infrared rays radiated by large amounts of carbon gases peaking at a wavelength of 4.3µm~4.5µm with a 2~15H fluctuation. This is caused by the combustion of materials and is known as CO_2 resonance radiation as indicated in the diagram below.

Çetin, A. Enis, et al. "Video fire detection–review." *Digital Signal Processing* 23.6 (2013): 1827-1843.

Step ④ Profile Embedding (4-1)

- **Example) Disaster Profile for Flood**

(Flood, Flood Symptom

{

(color, (R>G>B) & (|R-B|≥ 90) & (|G-B| ≥40, 1) ,
(ripple pattern, (R > 190) & (G > 100) & (B < 180), 1) ,
(color change , $R_t(x,y) > R_{mean}$, 0)

(object shifting, 4.3μm~4.5μm, 2~15H fluctuation)
(weather
(tides
(Season
(measure
(value
(Min flood depth
(Max flood depth

}

Trained Image Location)

Step ④ Profile Embedding (5)

- **Example *Disaster Symptom Profile*. (Earthquake)**

Element Name	Description	Examples
Disaster Type	Type of the Disaster	Earthquake
Symptoms	Observable State of the Environment suc h as Temperate, Object Shifting, Noise, e tc. (Symptom Attribute, Value Range, Annot ation, image(optional))	(waveform height, ,) (smoke, ,) (color of fire, ,) (Temperature Change, (Color Change, (Object Shifting,
Characteristics	Additional Description of the Disaster	

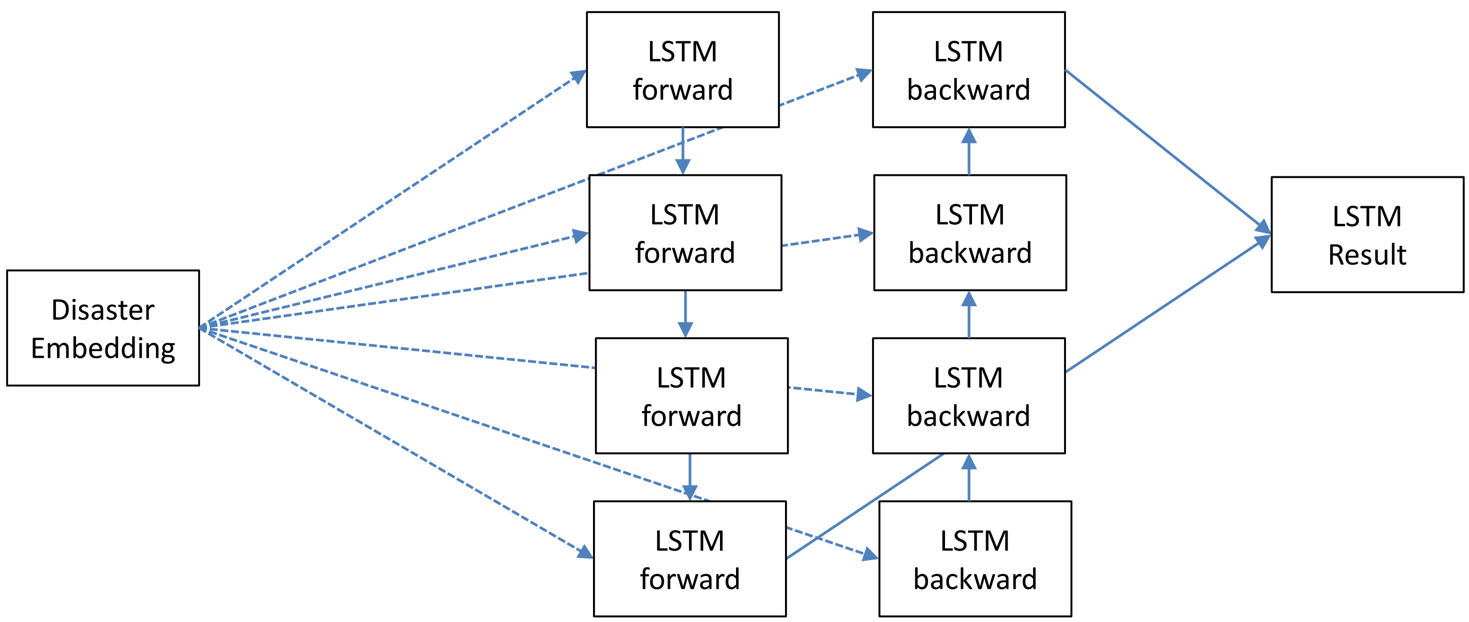
Step ④ Profile Embedding (6)

- **Example *Disaster Symptom Profile*. (Build Demolishing)**

Element Name	Description	Examples
Disaster Type	Type of the Disaster	Build Demolishing
Symptoms	Observable State of the Environment such as Temperate, Object Shifting, Noise, etc. (Symptom Attribute, Value Range, Annotation, image(optional))	(impulsion, (Object Shifting, (Color, ,) (Color Change, (Object Shifting,
Characteristics	Additional Description of the Disaster	

Step ⑤ Bidirectional LSTM (1)

- **We model the sequence in both directions (forward and backward) LSTM[1] (Long Short term Memory)**
  - **Bidirectional LSTM process the data in both directions with two separate hidden layers, which are then feed forwards to the same output layer.**



[1] Yu, Zhou, et al. "Using bidirectional LSTM recurrent neural networks to learn high-level abstractions of sequential features for automated scoring of non-native spontaneous speech." Automatic Speech Recognition and Understanding (ASRU), 2015 IEEE Workshop on. IEEE, 2015.

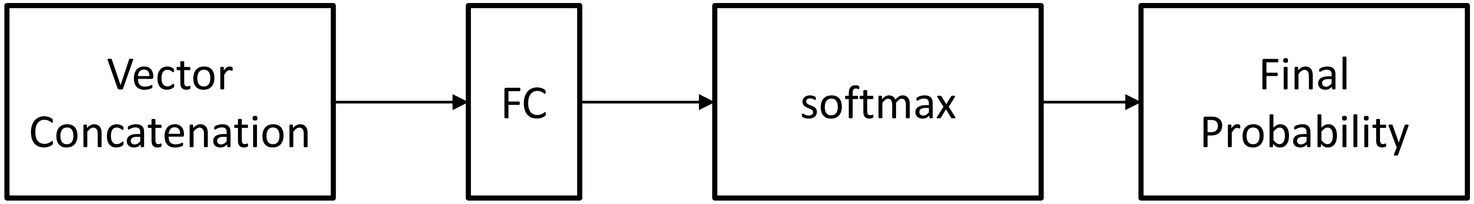
Step ⑤ Bidirectional LSTM (2)

- LSTM[1] was proposed in 1997 by Sepp Hochreiter and Jürgen Schmidhuber and improved in 2000 by Felix Gers' team
- Long short-term memory (LSTM) units are units of a recurrent neural network (RNN).
- An RNN composed of LSTM units is often called an LSTM network. A common LSTM unit is composed of a cell, an input gate, an output gate and a forget gate. The cell remembers values over arbitrary time intervals and the three gates regulate the flow of information into and out of the cell.
- As of 2016, major technology companies including Google, Apple, and Microsoft were using LSTM as fundamental components in new products.
- For example, Google used LSTM for speech recognition on the smartphone, for the smart assistant Allo and for Google Translate. Apple uses LSTM for the "Quicktype" function on the iPhoneand for Siri. Amazon uses LSTM for Amazon Alexa.

[1] https://colah.github.io/posts/2015-08-Understanding-LSTMs/
https://en.wikipedia.org/wiki/Long_short-term_memory

Step ⑥ Detecting Disaster (1)

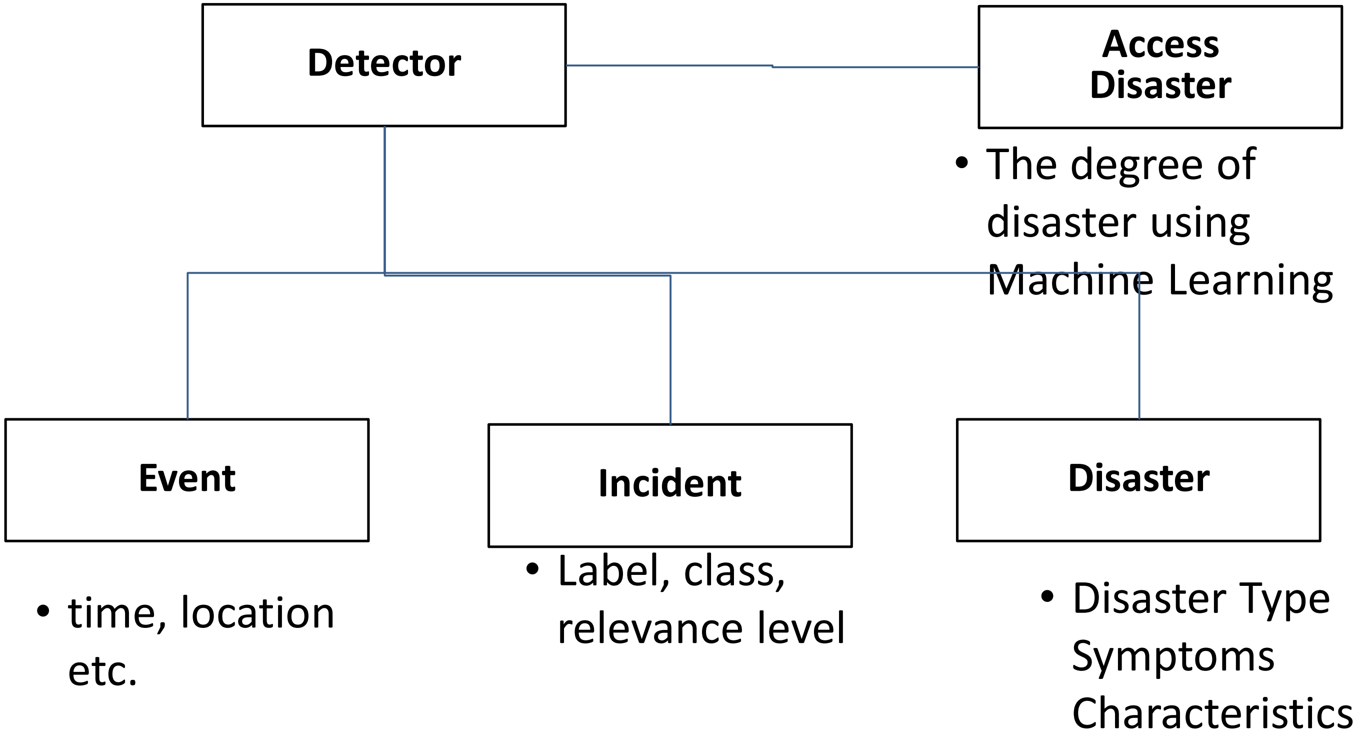
- **Detecting Disaster**
  - **Concatenate the image and text features followed by a fully connected layer and a softmax classifier**
  - **To give a final probability and Image of the sample containing relevant information about a disaster.**



Step ⑥ Detecting Disaster (2)

• Detecting Disaster

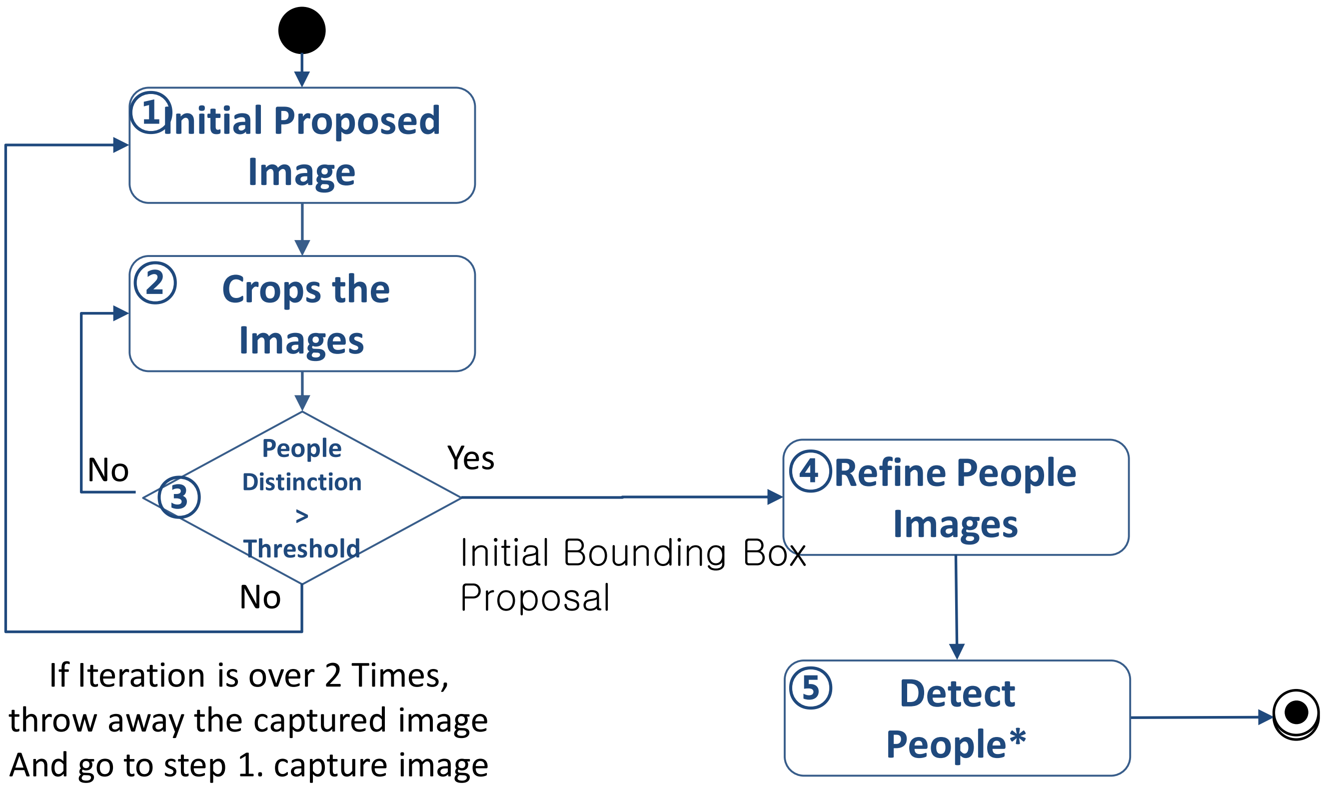
- **Collect a comprehensive set of measurements under disaster.**
- **Distinguish and Detect Disaster using pre-defined feature**



Unit 5.2
People Detection

Process for Detecting People (1)

- **Process for Detecting People based on GAN[1]**



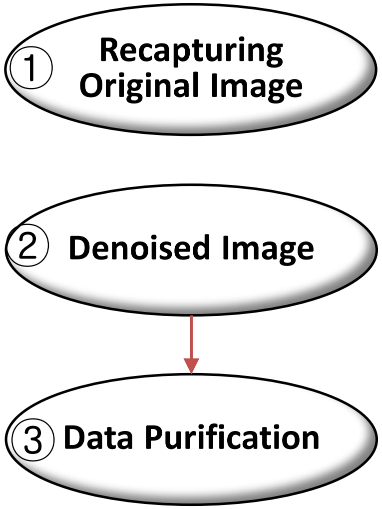
[1] Goodfellow, Ian, et al. "Generative adversarial nets." Advances in neural information processing systems. 2014.

Process for Detecting People (2)

- To detect people, our process is
  - Step ① Initial Proposed Image
  - Step ② Initial Proposal (with Super Resolution, deblurring & denoising)
  - Step ③ Distinct People on cropped image
  - Step ④ Refine People Image
  - Step ⑤ Detect People

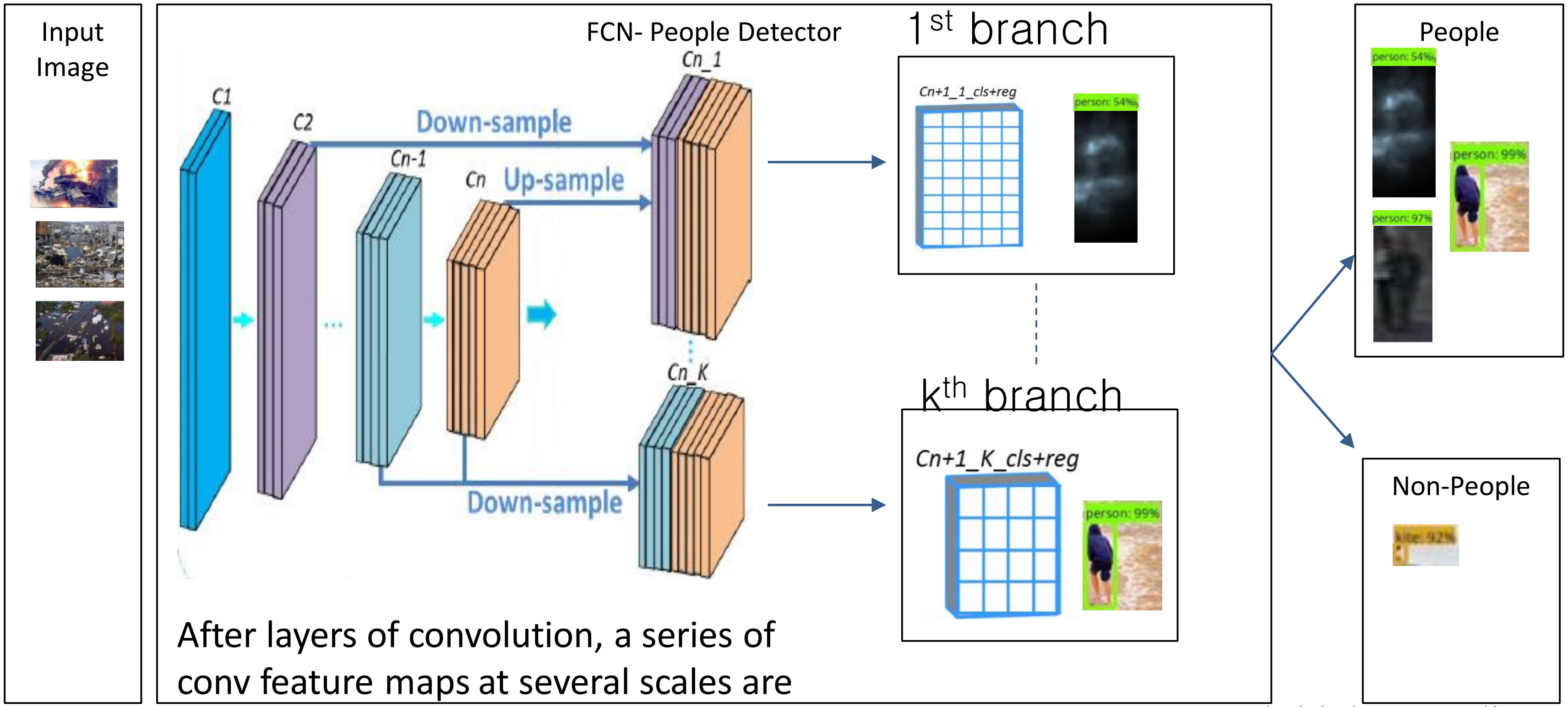
Step ① Initial Proposed Image

- **Gather Image Data from denoised image**
  - **Get an Image data from denoised**
  - **Data Purification : detecting and correcting (or removing) corrupt or inaccurate record**
  - **If Denoised image is not so good for use as a people detection process, recapturing original image for later step.**



Step ② Crops the Images

- **Crop the images Based on Multi-Branch Fully Convolutional Network[1]**



After layers of convolution, a series of conv feature maps at several scales are generated

Initial Bounding Box Proposal

[1] Bai, Yancheng, and Bernard Ghanem. "Multi-branch fully convolutional network for face detection." arXiv preprint arXiv:1707.06330 (2017).

Step ③ Distinct People on cropped image

- **Algorithm of People Distinction**

Algorithm 2 People Distinction

Input : ***Initial bounding box proposal***

- **Initialization:**
  1) iteration Count = 0;
- **While not** compute **do**
  1) Iteration count ++;
  2) $people\ distinction\ count = f(bounding\ box\ proposal)$
  3) if $people\ distinction\ count > 1$ *and*
     Person probability ratio on input then
     Refinement ;

  else *continue;*

End while

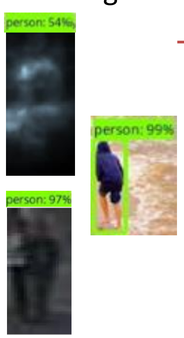
Output : $\boldsymbol{Initial\ bounding\ box\ proposal}$

Step ④ Refine People images

• Refinement Image Model

- **Our generator network for refinement includes two components**
  - Up-sample sub-network : takes the low-resolution images as the inputs and the outputs are the super-resolution images
  - Refinement sub-network : to refine the super-resolution images from the up-samples network

People Images



Generator Network

Up-Sample sub-network [Ledig, 2017, 1]

Similar to [Ledig, 2017]

1) There are two fractionally-strided convolutional layers (i.e. de-convolutional layer) in the network
2) Each deconvolutional layer perform up-sampling a low-resolution image to a 4× super resolution image.

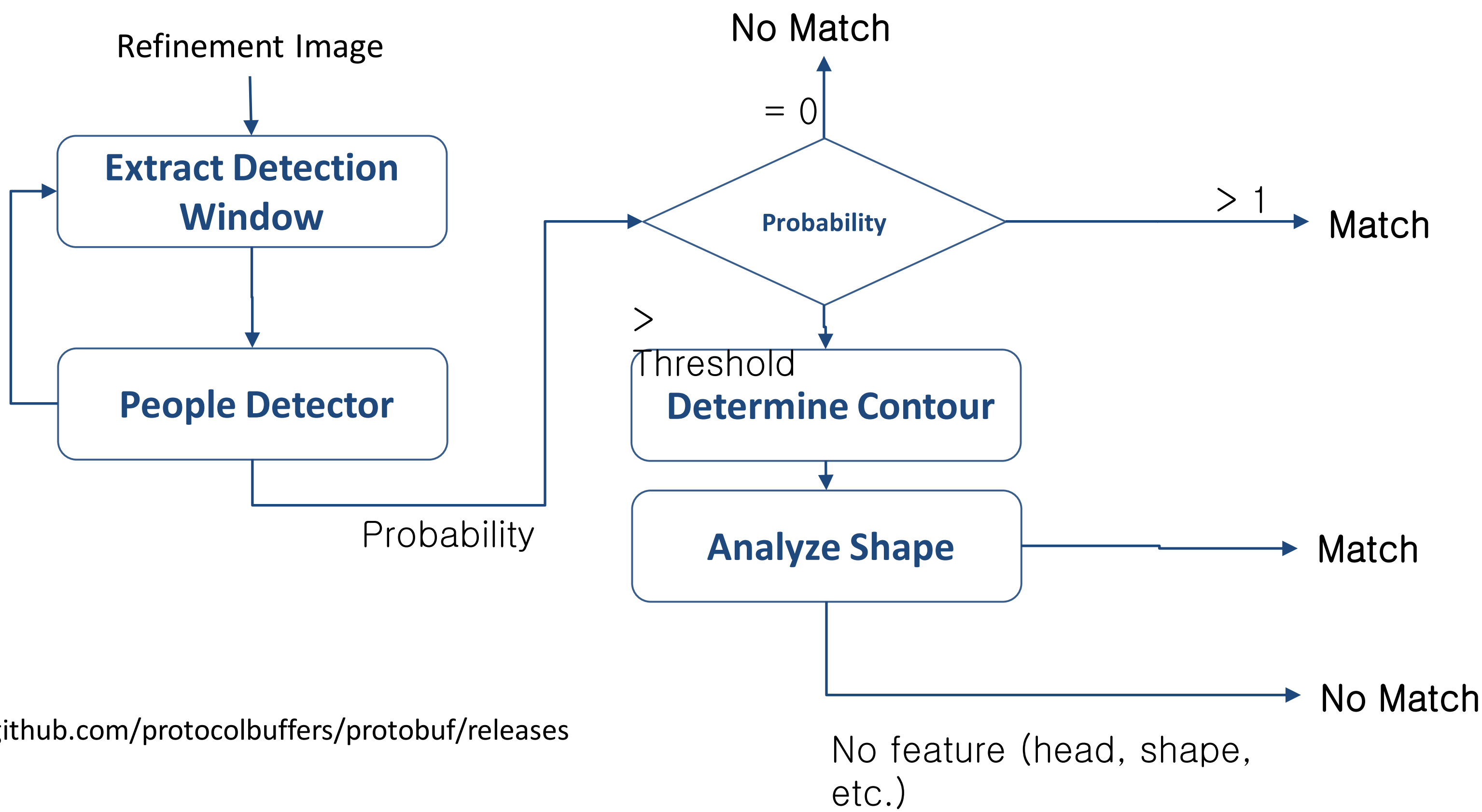
Proposed Added Refinement Network for improving Accuracy

The refinement sub-network processes the blurring image, and outputs a clear super-resolution image, which is easier for the discriminator to classify the People vs. non-People objects.

[1] Ledig, Christian, Lucas Theis, Ferenc Huszár, Jose Caballero, Andrew Cunningham, Alejandro Acosta, Andrew P. Aitken et al. "Photo-Realistic Single Image Super-Resolution Using a Generative Adversarial Network." In CVPR, vol. 2, no. 3, p. 4. 2017.

Step ⑤ Detect People

- **Detecting people in an Image**
  - **A small region of the image is extracted(called detection window)**
  - **The detector uses the google protocol buffer framework[1] to determine if the detection windows contains a people**



[1https://github.com/protocolbuffers/protobuf/releases

Unit 6
Design for Quality Requirements

My proposal for Quality Requirement

- **High accuracy**
  - 1) Convert Blur or Noise image to clear and Super Resolution Image
  - 2) Use Not only Image but also Profile textual context

- **Time Efficiency**
  - 1) Removing unimportant steps or refinement step at initial proposed phase.
  - 2) Uses initial proposed image for people detecting

Unit 6.1
Design for High Accuracy

Design for Accuracy(1)

- **Up-sample resolution**
  - 4 x Up-scaling
    Use the super-resolution network to generate clear and fine people with high resolution (4× up-scaling)
- **Refinement Network**
  - Our refinement network plays two roles:
    The first role is to promote the generator network to reconstruct sharper images.
    The Second is to provide the high-resolution images to the people detector, including both the generated and the natural real high-resolution images, people or non-people in the discriminator network.

Unit 6.2
Design for Time Efficiency

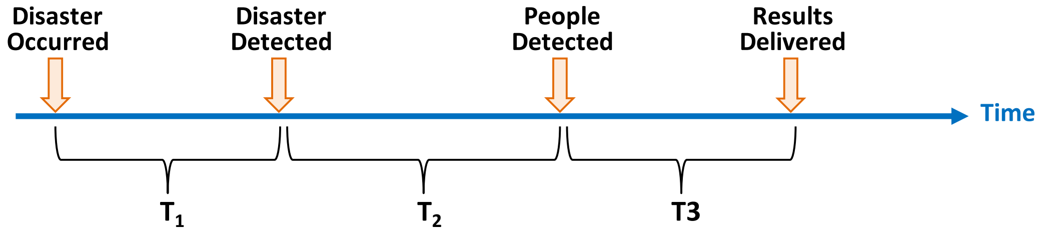
Design for Time Efficiency

• Timeliness in Disaster Analytics

- Time to detect disaster
- Time to detect people and their locations
- Time to deliver the analytics results

• Minimize the total time, Tsum

- $T_{sum} = T_1 + T_2 + T_3$



Unit 7.
PoC Implementation & Experiments

PoC Environment

- **PoC Implementation**
  - **To develop key components for detecting of disaster and people**
    - Image Converter Component
    - Detection Model Building Component
    - Event Learning Component
    - Detection Model Component
  - **To experiments the framework using the proposed design**

Category	Item	Description
Language	Python	Development Language and algorithm Library
Database	SQLite3, Hive	Event Transaction Store and learning Result store
Data Processor	Apache Spark	Large scale data processing
Web Server	Tornado	Web Socket server

PoC Experiment

- **Experiment in terms of efficiency and accuracy improvement in people and Disaster detection**
  - **Training Data and Test Data Set**
  - **To compare accuracy of detecting People and Disaster**
    - Result of Disaster Detection
    - Result of People Detection
  - **To compare efficiency of detection**
    - Compare Average/Max Learning Time between Proposed Services and Well known algorithm for Detecting

Unit 8.
Assessment

Assessment

- **Assessment in terms of efficiency and accuracy improvement in people and Disaster detection**
  - **Accuracy and Efficiency of Disaster detection**

Cases		Avg. Learning Time (msec)	Result of Disaster Detection	Result of People Detection
Without Framework	SVM			
	RFR			
	Bayesian			
	Decision Tree			
With Framework	SVM			
	RFR			
	Bayesian			
	Decision Tree			
	Proposed Disaster Detection Service			
	Proposed People Detection Service			

Thank you.

Woo Young Moon

Department of Computer Science and Engineering

Soongsil University