# CrowdLearn: A Crowd-AI Hybrid System for Deep Learning-based Damage Assessment Applications

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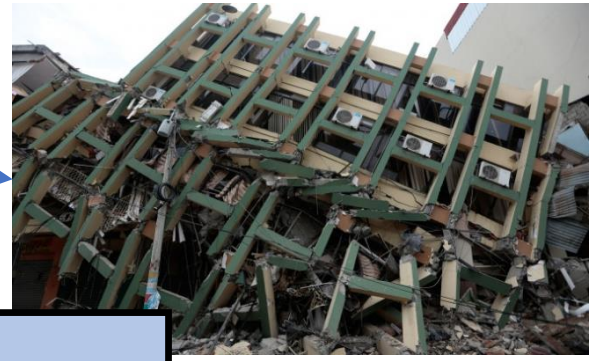
# Background: Disaster Response

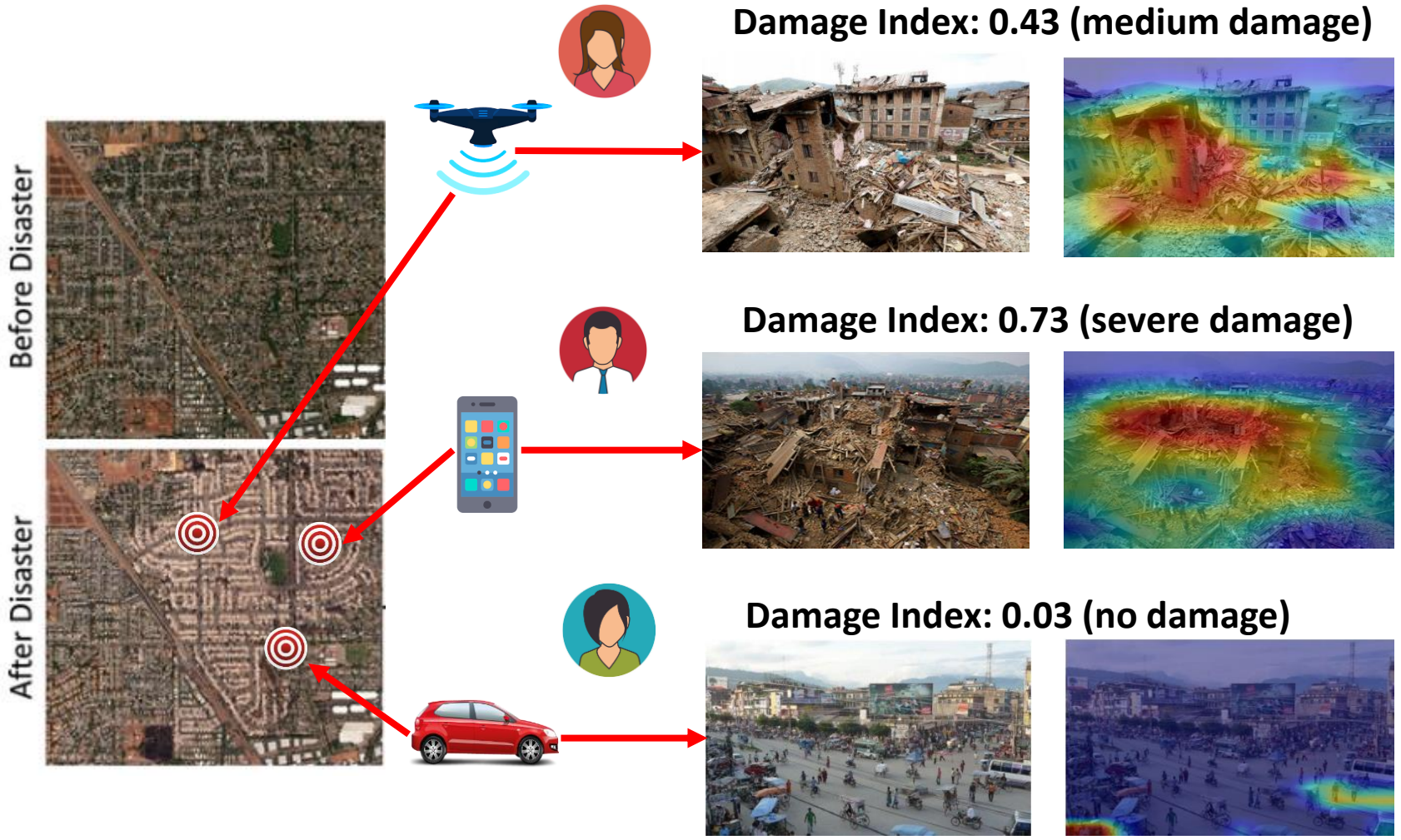
- **In disaster-related events (e.g., hurricanes, tornados), severe damages could simultaneous happen in many places.**
  - Broken bridge, damaged houses, fires, accidents
  - Require immediate attention from response teams (e.g., FEMA, Police, Ambulance)



How to prioritize the response team's operations?

# The Disaster Damage Assessment (DDA) Application

A new sensing application of automatically identifying the areas of maximum damage given images to prioritize rescue operations.



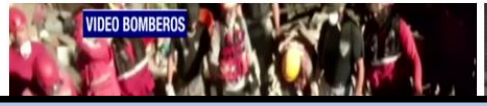
# Motivation – Limitation of AI

- We found existing DDA applications cannot deliver satisfactory accuracy and are prone to various failure scenarios.
  - Cannot distinguish fake images (Figure 2(a))
  - Easy to be mislead by camera angles (Figure 2(b))
  - Confused by low-resolution images (Figure 2(c))
  - Fail to understand implicit stories (Figure 2(d))

(a) Fake Image

(b) Close Up

| Figure | Actual | Reported |
|---|---|---|
| a | no | severe |




(c) Low Resolution

(d) Implicit

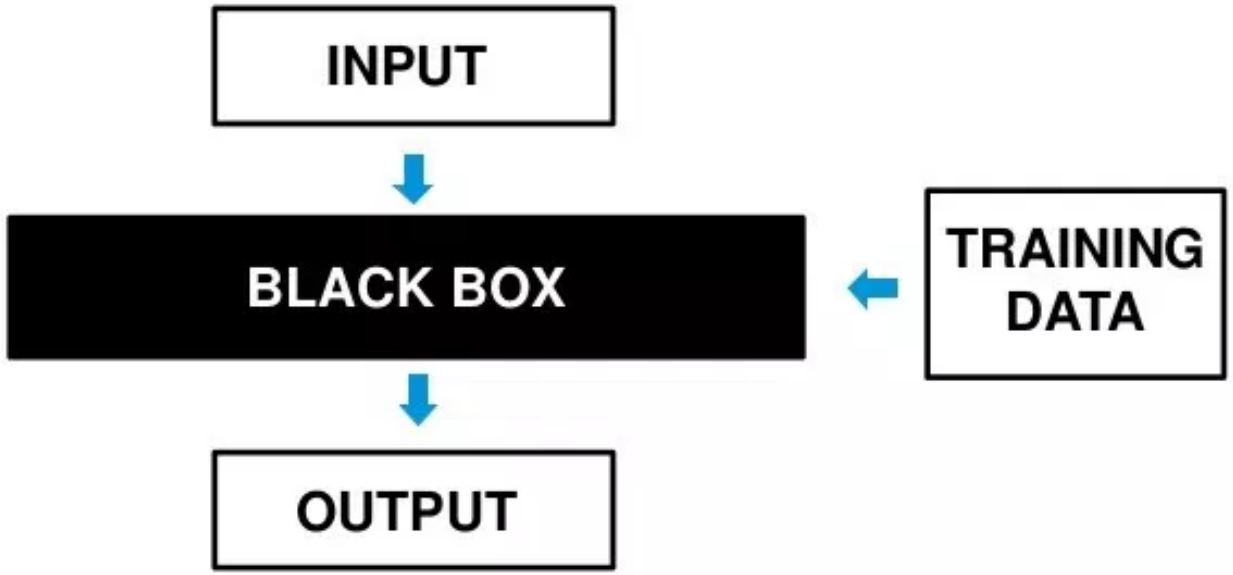
**Motivation: Can Human Intelligence (HI) help AI to deliver better DDA performance?**

**Wrong Outputs of AI** **Failure Scenarios of AI**

- Human on the other hand, can more reliably assess the actual scene described by the image and report the correct damage severity.

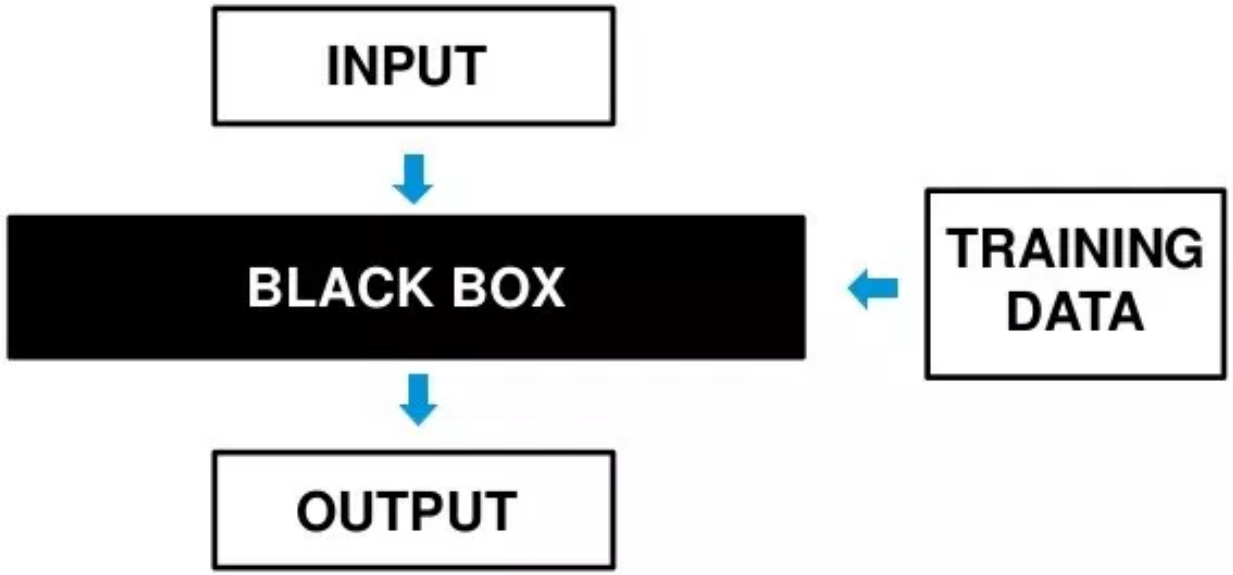
# Challenge 1: Black-Box AI

- The lack of interpretability of the results from AI algorithms makes it extremely hard to diagnose the failure scenarios such as performance deficiency.
  - Why the AI model fails? Is this due to lack of training data or the model itself?
  - How to identify and fix the failure scenarios?



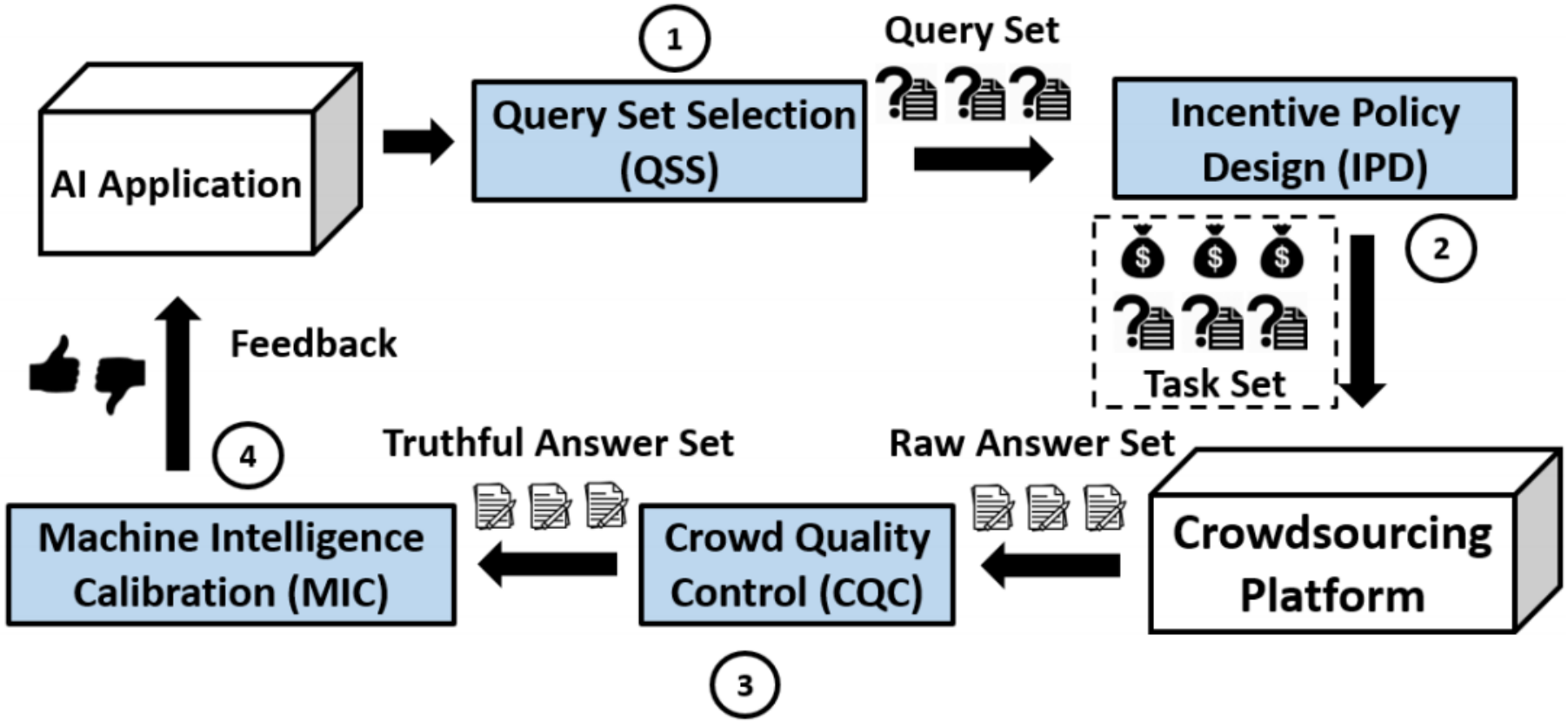
# Challenge 2: Black-Box HI

- the lack of control of crowdsourcing platform makes it difficult to acquire high quality and timely human intelligence.
  - Cannot directly select and manage the workers.
  - The time and quality of the responses from the crowd workers are highly dynamic and unpredictable.



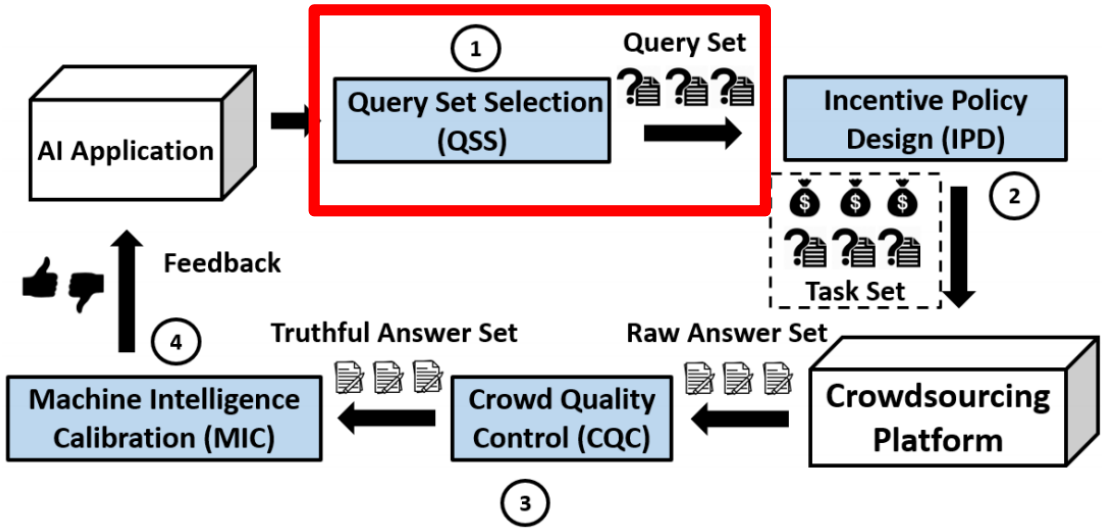
# The CrowdLearn Framework

- A Closed-loop crowd-AI hybrid system
- The AI algorithms selectively identify a subset of data to query the crowd
- The crowd's response is used to tune the AI model



# Query Set Selection (QSS) Module

- QSS selects a set of images to query the crowd.
  - We select a diverse set of AI Algorithms for DDA as a committee
  - Each committee  member votes for the label of the image
  - Pick the images that the committee has the most disagreement



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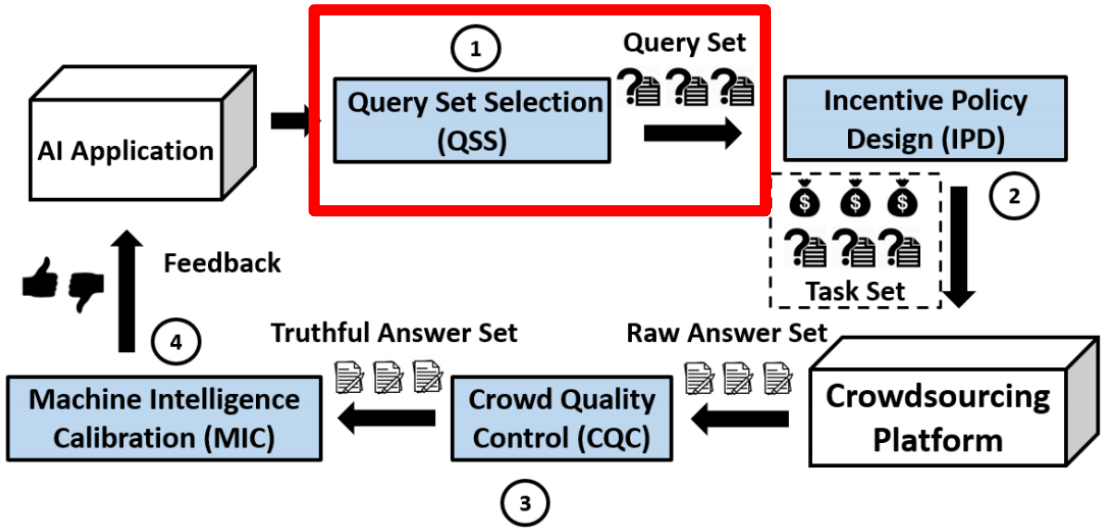
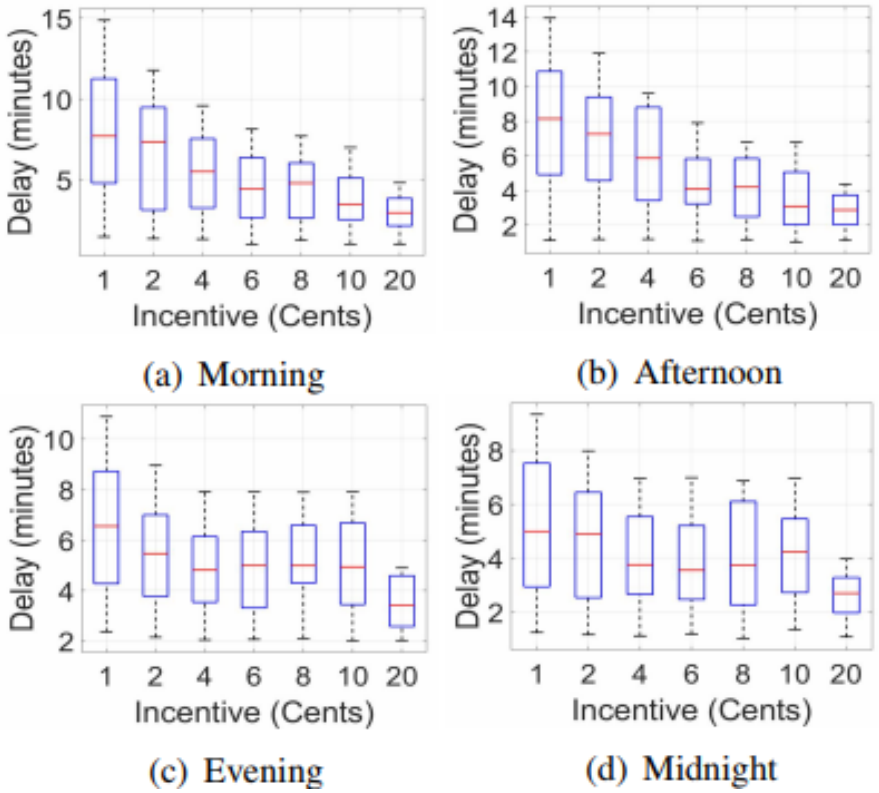
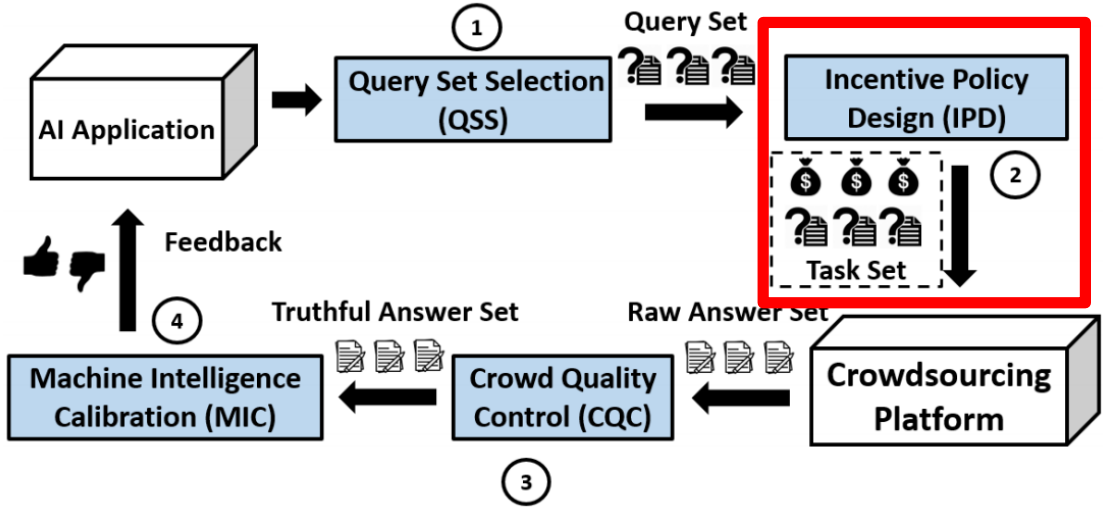


# Incentive Policy Design (IPD) Module

- IPD assigns the optimal incentive for each query to be sent to the crowdsourcing platform to get most timely response.
  - We observe that the incentive is context-aware and the expected level of incentives depends on time of the day.
  - We develop a Contextual Multi-armed Bandit to identify the optimal incentive for each query.



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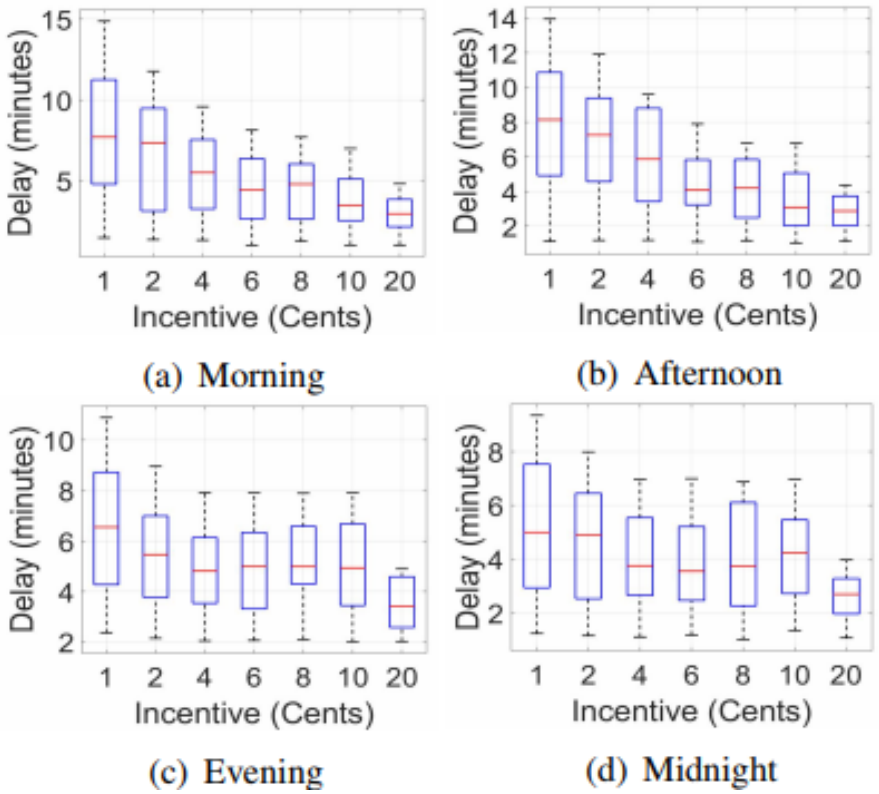
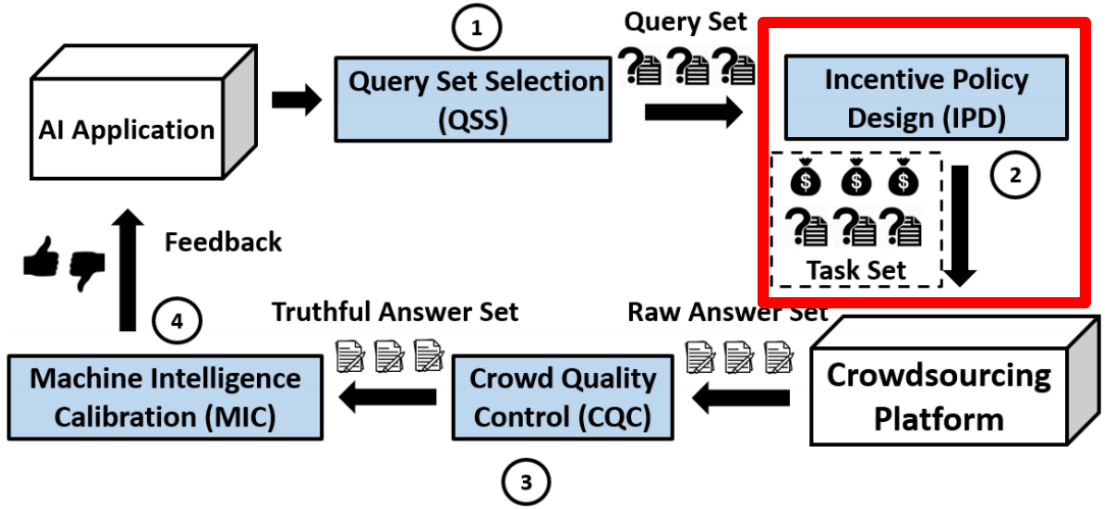
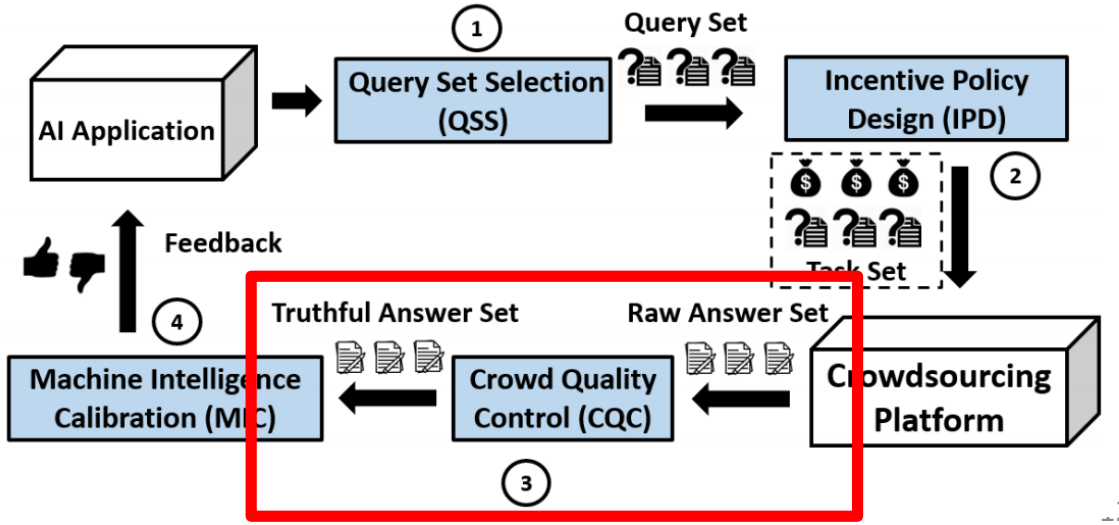


# Crowd Quality Control (CQC) Module

- CQC takes the answers from the crowd and provides quality control to generate truthful answers.
  - We collected both the label and contextual information about an image from human.
  - The label and contextual information are fed into a classifier (XGBoost) to decide the truthful label.

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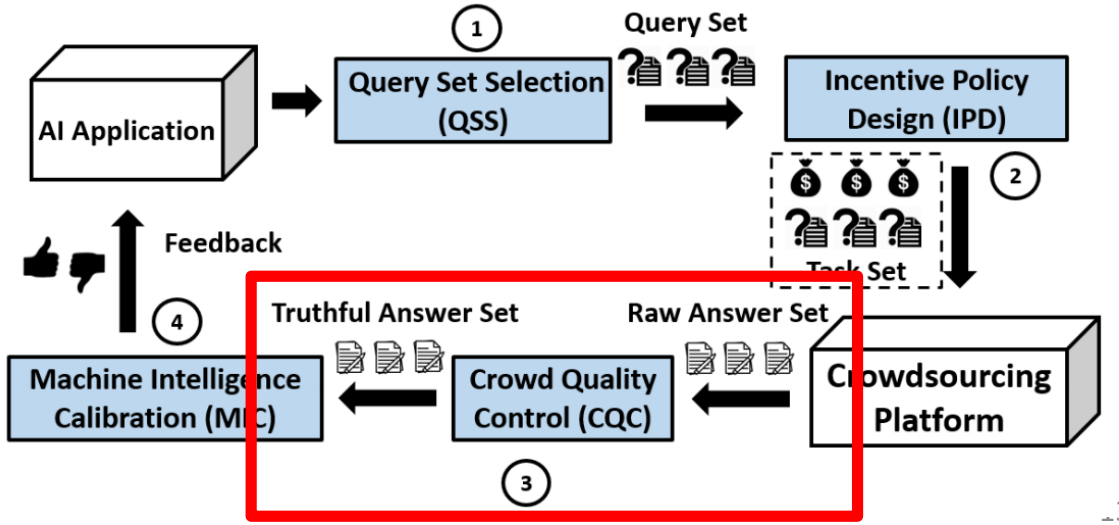
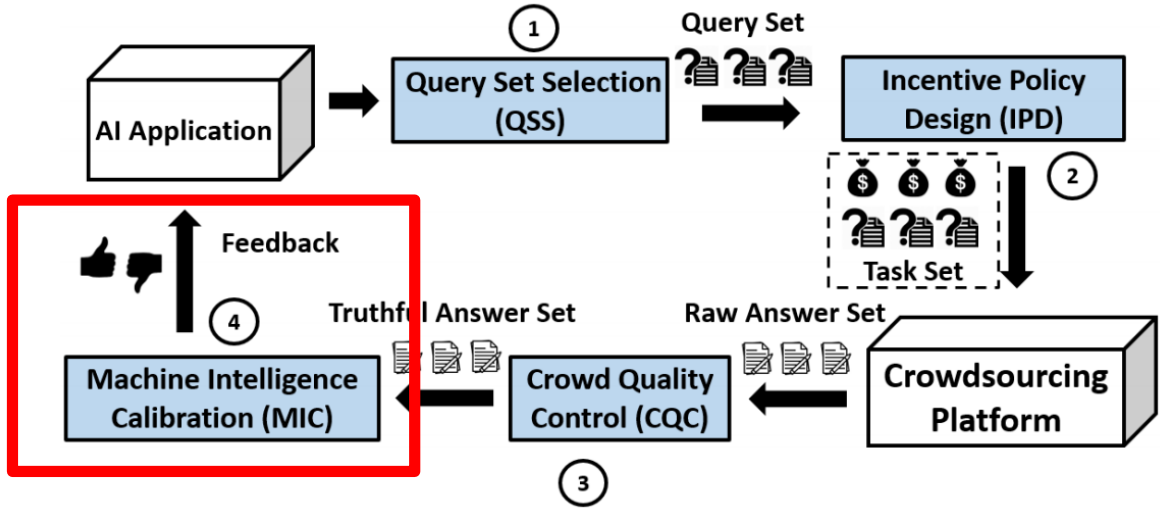


# Machine Intelligence Calibration (MIC) Module

- MIC compares the crowd answers with the results of the AI algorithms and improves AI.
  - Retrain the models with the new labels collected from CQC.
  - Update the expert weights of the AI algorithms in the committee.



# Evaluation

**Dataset**: 3,000 social media images collected from Equator earthquake

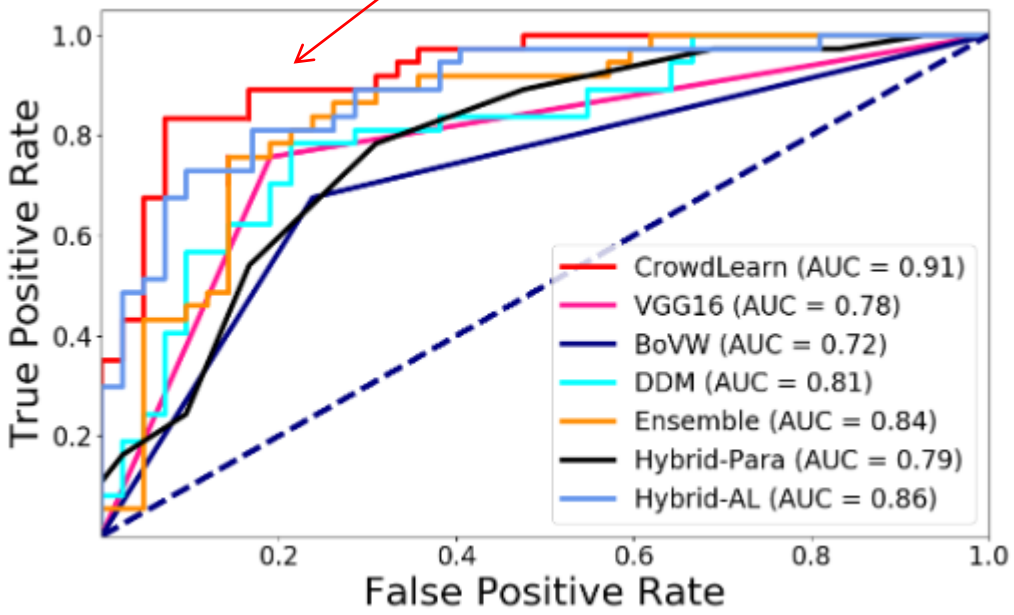
**Baselines**:

- **VGG16**: A DDA scheme that uses deep Convolutional Neural Networks (CNN)
- **BoVW**: A DDA scheme that uses handcrafted features (e.g., scale invariant feature transform, histogram of oriented gradients) to train a neural network classifier
- **DDM**: A DDA scheme that combines CNN and Gradient-weighted Class Activation Mapping (Grad-CAM) to produce a damage heatmap of a given image, which is used to derive the damage severity
- **Ensemble:** An aggregation of the above algorithms (VGG16, BoVW, DDM)
- **Hybrid-Para:** human-AI hybrid system where humans and AI independently label the images
- **Hybrid-AL**: a crowdsourcing-based active learning framework for AI algorithms where the annotated labels collected from MTurk are used to re-train the AI algorithm for the performance improvement

**Crowdsourcing Platform – Amazon Mechanical Turks**

# Results – Effectiveness

Our Solution




**ROC Curve**

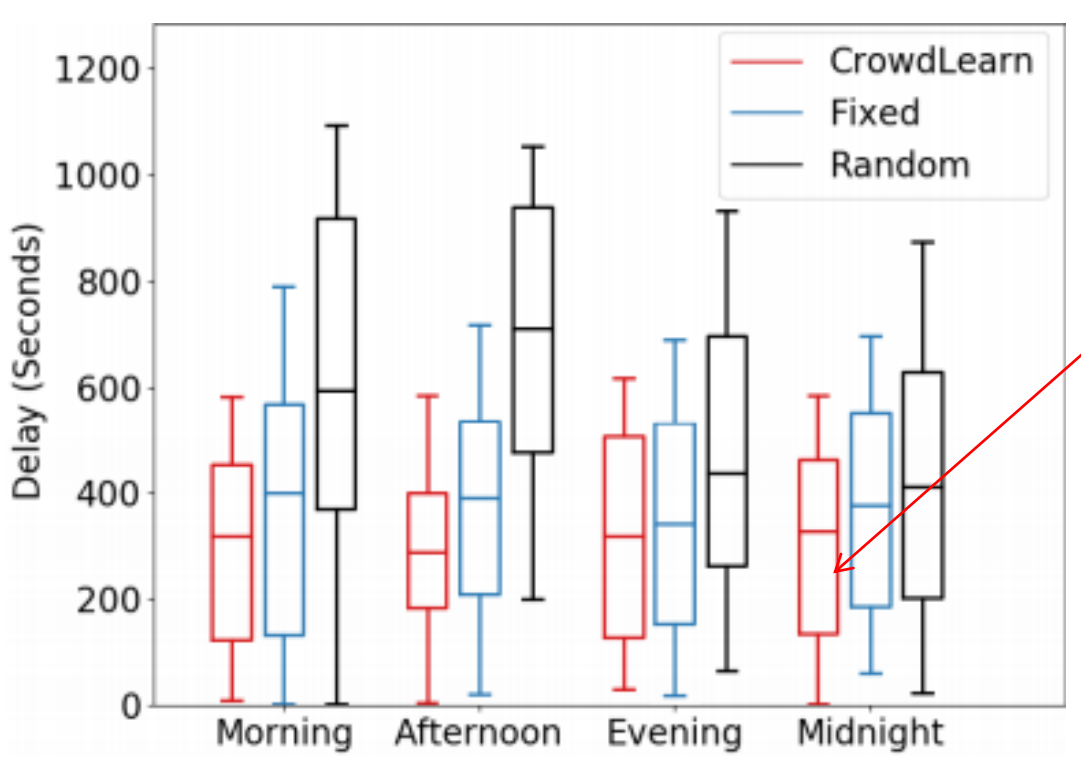
Our Solution

| Algorithms | Accuracy | Precision | Recall | F1 |
|---|---|---|---|---|
| **CrowdLearn** | **0.877** | **0.904** | **0.885** | **0.894** |
| VGG16 | 0.770 | 0.845 | 0.744 | 0.791 |
| BoVW | 0.670 | 0.707 | 0.744 | 0.725 |
| DDM | 0.807 | 0.891 | 0.765 | 0.823 |
| Ensemble | 0.815 | 0.892 | 0.778 | 0.831 |
| Hybrid-Para | 0.797 | 0.849 | 0.795 | 0.821 |
| Hybrid-AL | 0.823 | 0.883 | 0.803 | 0.841 |

**Accuracy, Precision, Recall, and F1**

**Our solution achieves better detection effectiveness.**

# Results – Delay vs. Context




**Our Solution**

**Crowd Delay w.r.t Temporal Contexts**

**Our solution achieves lower delay in various temporal contexts.**

# Thank You!

## Social Sensing Lab@ Notre Dame

https://www3.nd.edu/~sslab/