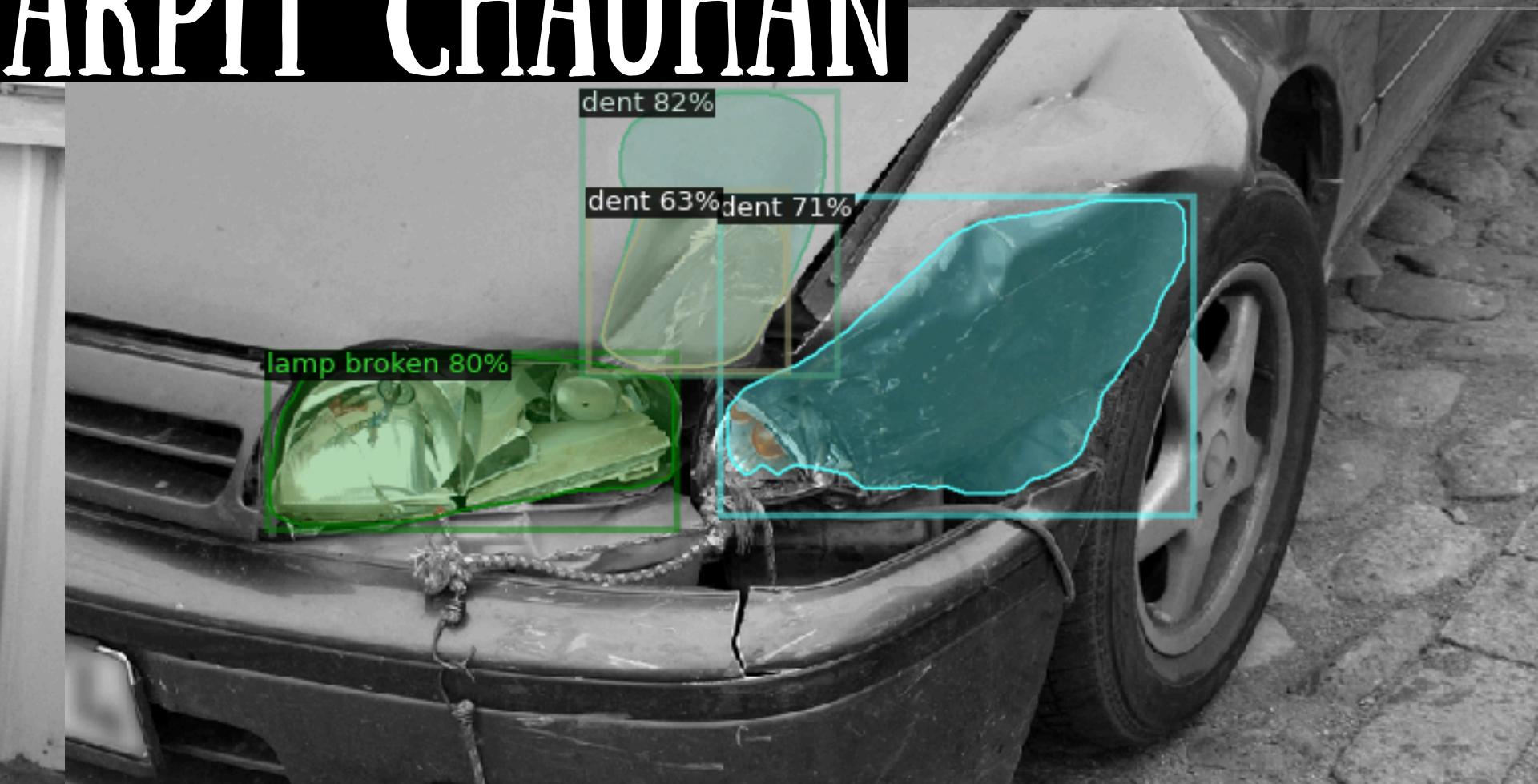
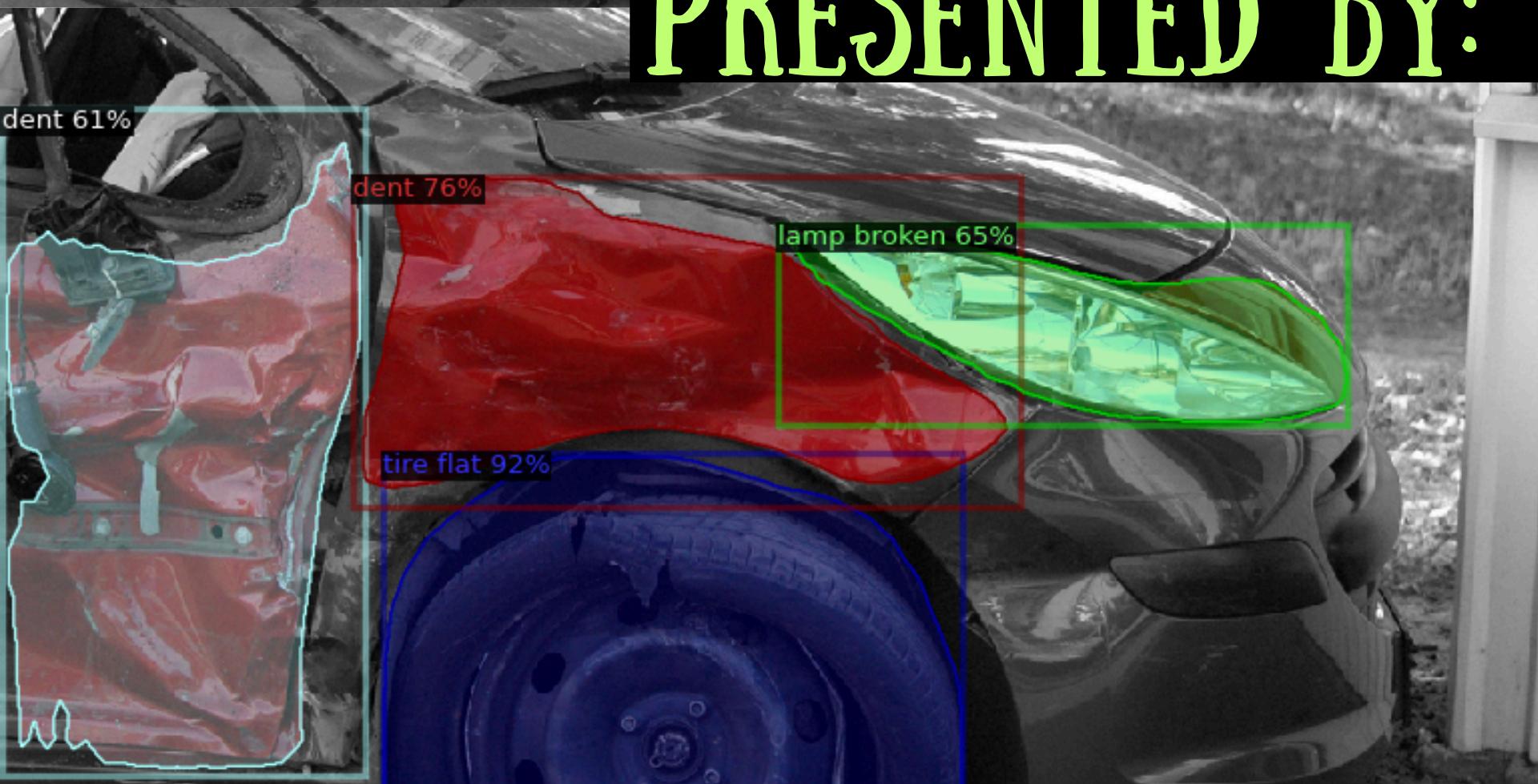


TITLE :AUTOMATED VEHICLE DAMAGE ANALYSIS AND COST PREDICTION WITH MASK R-CNN

GUIDE: DR. AMOL JOGLEKAR
PRESENTED BY: ARPIT CHAUHAN



INTRODUCTION & PROBLEM STATEMENT

INTRODUCTION

- Vehicle insurance claim processing is slow and inefficient, requiring manual inspections and paperwork.
- Policyholders experience long wait times, while insurance companies struggle with fraudulent claims and operational delays.
- Traditional methods are costly, inconsistent, and prone to human errors.
- AI-driven solutions can revolutionize the damage detection and cost estimation process.



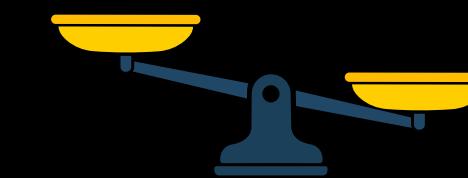
- Claim Initiation
- Manual Inspection
- Paperwork Processing
- Wait Time
- Fraud Detection
- Operational Delays
- AI Solution Implementation
- Improved Efficiency

1. DELAYS AND HIGH OPERATIONAL COSTS.

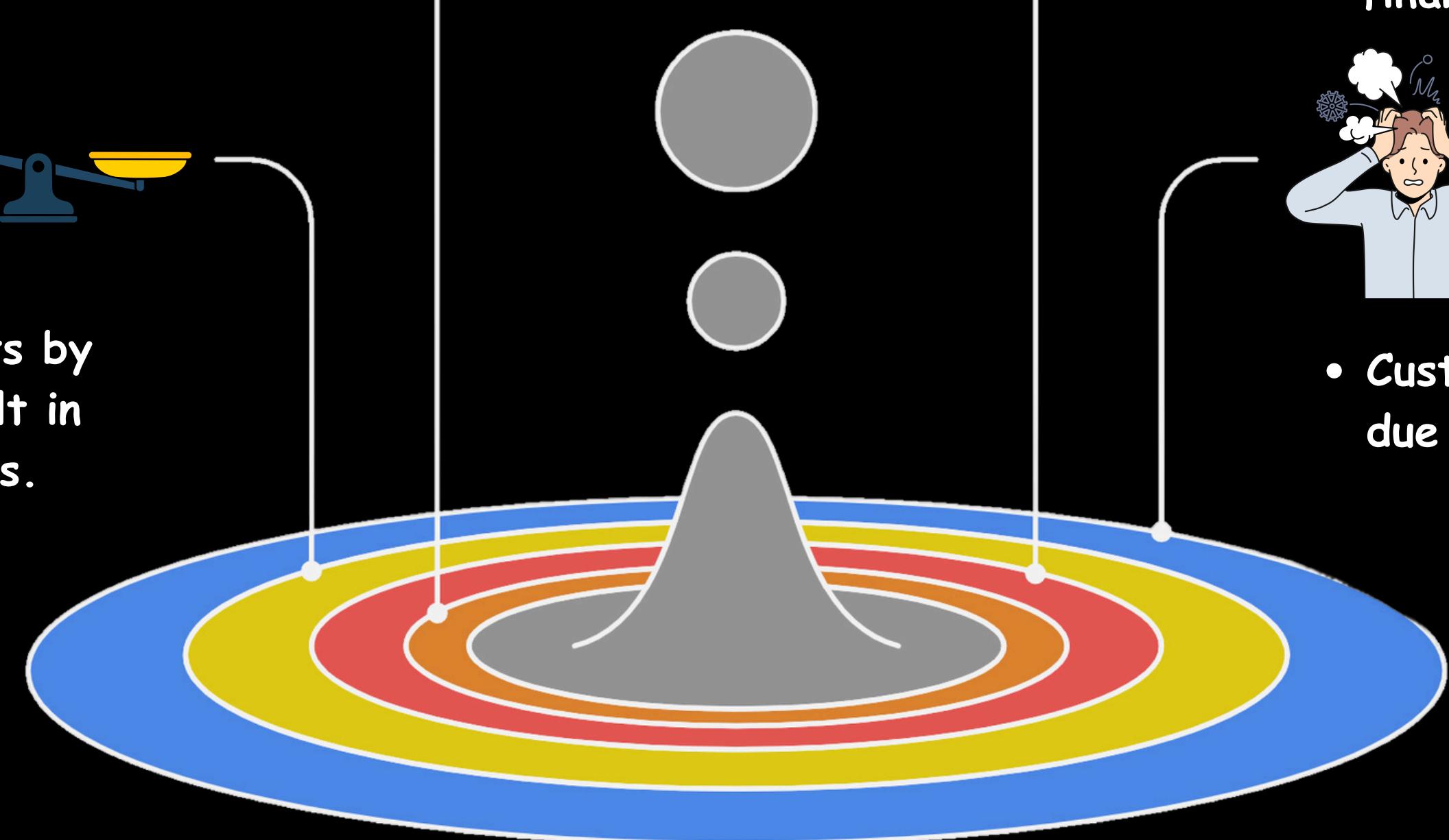


- Manual inspections lead to delays and high operational costs.

2. INCONSISTENT EVALUATIONS



- Subjective assessments by human inspectors result in inconsistent evaluations.



3. FINANCIAL LOSS

- Fraudulent claims increase financial losses for insurers.



4. CUSTOMERS FRUSTRATION

- Customers face frustration due to long processing times.

CHALLENGES-IN-VEHICLE-INSURANCE-CLAIMS

NEED_FOR_AUTOMATION_IN_DAMAGE_ASSESSMENT_&_COST_ESTIMATION

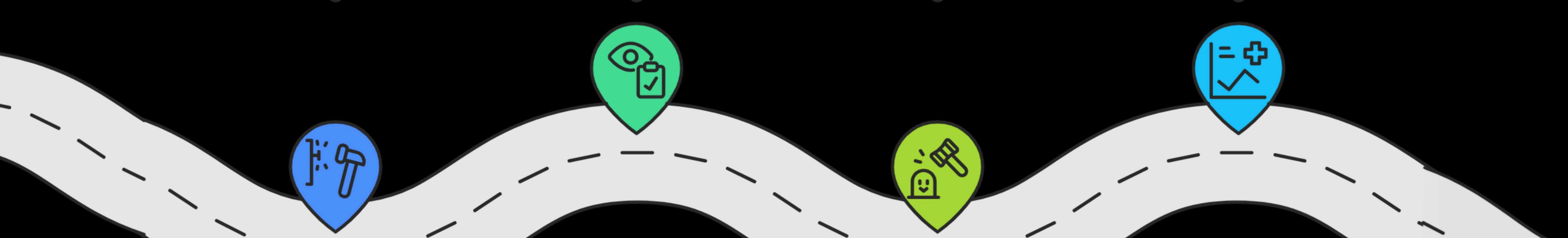
1. AI-based image processing provides fast, accurate, and reliable damage detection.
2. Automated assessments reduce dependency on human inspectors.
3. Cost estimation models help in fair and data-driven claim settlements.
4. Improves efficiency for insurance companies, car rental agencies, and repair shops.

AI-based image processing provides fast, accurate, and reliable damage detection

Automated assessments reduce dependency on human inspectors.

Cost estimation models help in fair and data-driven claim settlements.

Improves efficiency for insurance companies, car rental agencies, and repair shops.

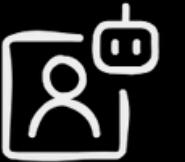


LITERATURE_&_RESEARCH_GAP



Manual Inspection

Traditional assessments rely on human inspections, causing delays and inconsistent cost estimations.



AI Adoption

Few AI models effectively segment damage, facing challenges from real-world factors.



Cost Prediction

Assessments depend on historical data, lacking real-time AI-driven repair cost estimation.



Model Accuracy

Existing models struggle with detecting small or unclear damages, limiting effectiveness.



Fraud Detection

Manual processing complicates fraud detection and slows claim settlements.

(Sources: Literature Review from previous studies on vehicle damage detection & repair cost estimation)

PROPOSED SOLUTION

Using Mask R-CNN for Vehicle Damage Detection

- Mask R-CNN is a deep learning model designed for instance segmentation.
- It detects and outlines damaged vehicle parts with high precision.
- Helps in automating the insurance claim process by providing accurate damage localization.

HOW_IT_WORKS

Vehicle Damage Analysis Process

Image Processing

The system analyzes images of damaged vehicles.



Damage Classification

AI categorizes the type of damage (dent, scratch, crack, etc.).

Object Detection & Segmentation

Mask R-CNN identifies and segments damage regions.

Cost Estimation

A machine learning model predicts repair costs based on detected damage.

IOU_FOR_REPAIR_COST_ESTIMATION

WHAT IS IOU?

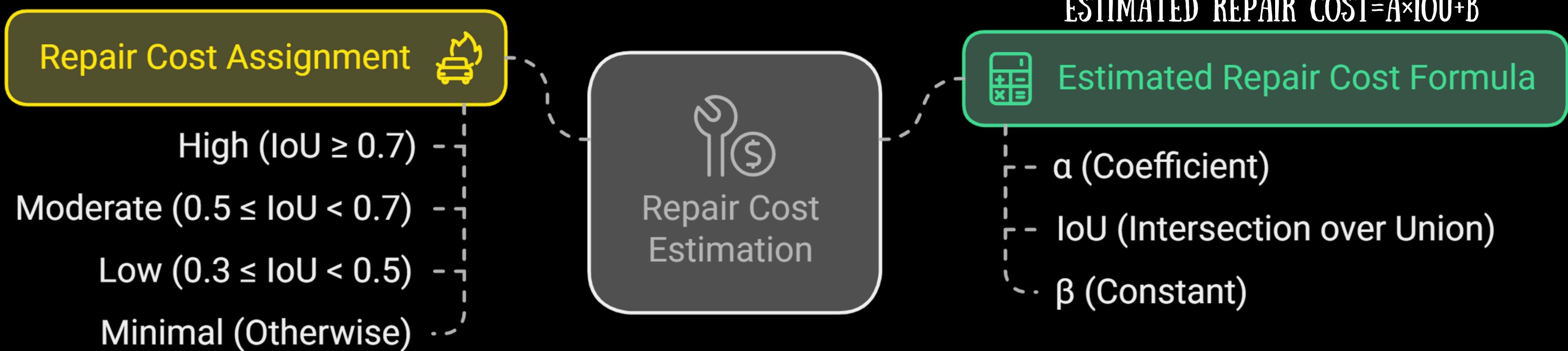
- Intersection over Union (IoU) measures the overlap between predicted damage regions and ground truth.
- Higher IoU → More severe damage → Higher repair costs.

MACHINE LEARNING FOR COST PREDICTION:

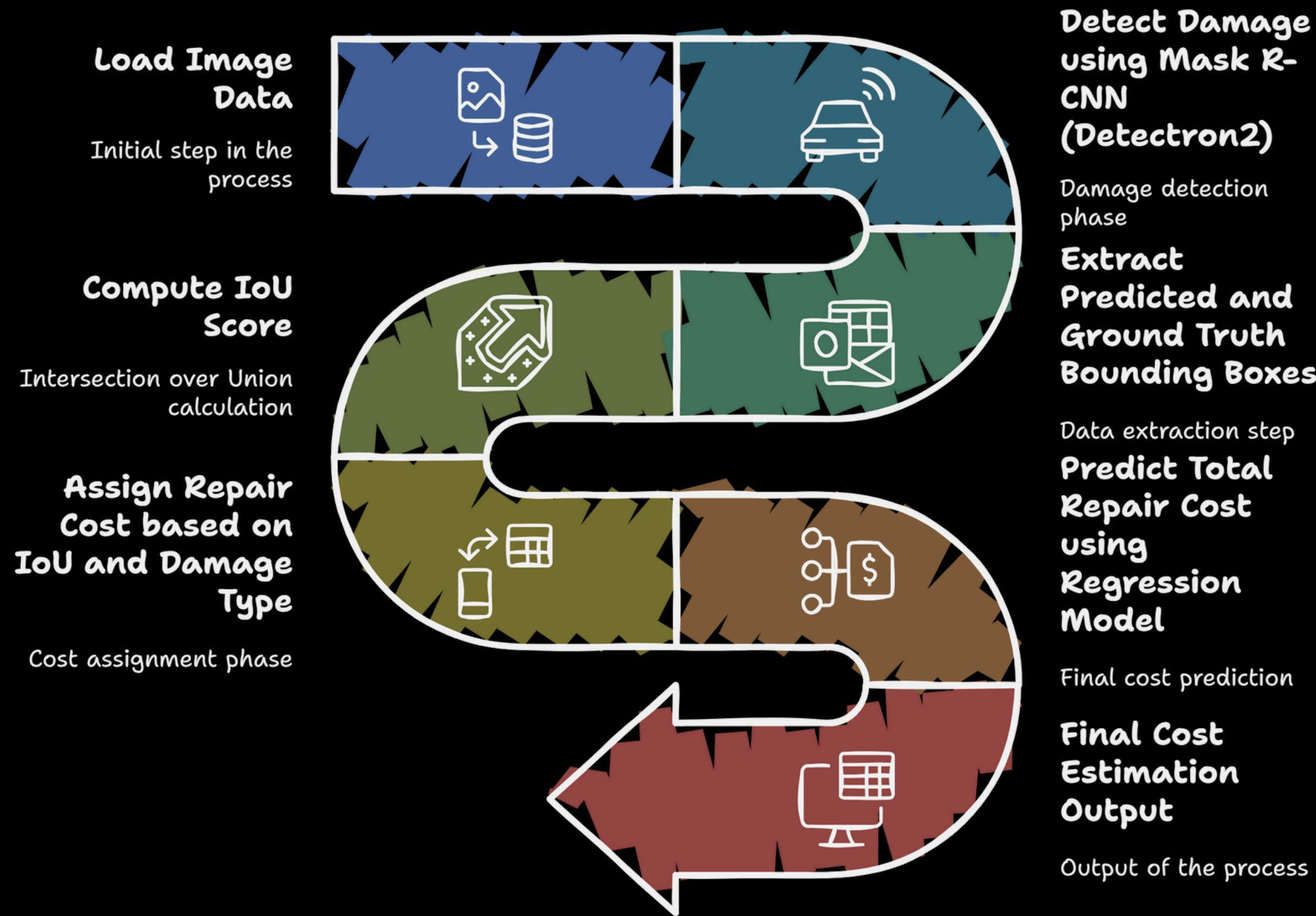
Regression model using bounding box features to predict repair costs.

FINAL COST CALCULATION:

$$\text{Total Repair Cost} = \sum_{i=1}^n C_{\text{repair},i}, \text{ (Where } n \text{ is the number of detected damages)}$$



-AUTOMATED_PIPELINE_FOR_INSURANCE CLAIMS



METHODOLOGY

- Data Preparation:
- Dataset split: Train (2,819), Validation (813), Test (377).
- Damage categories: Dents, scratches, cracks, etc.

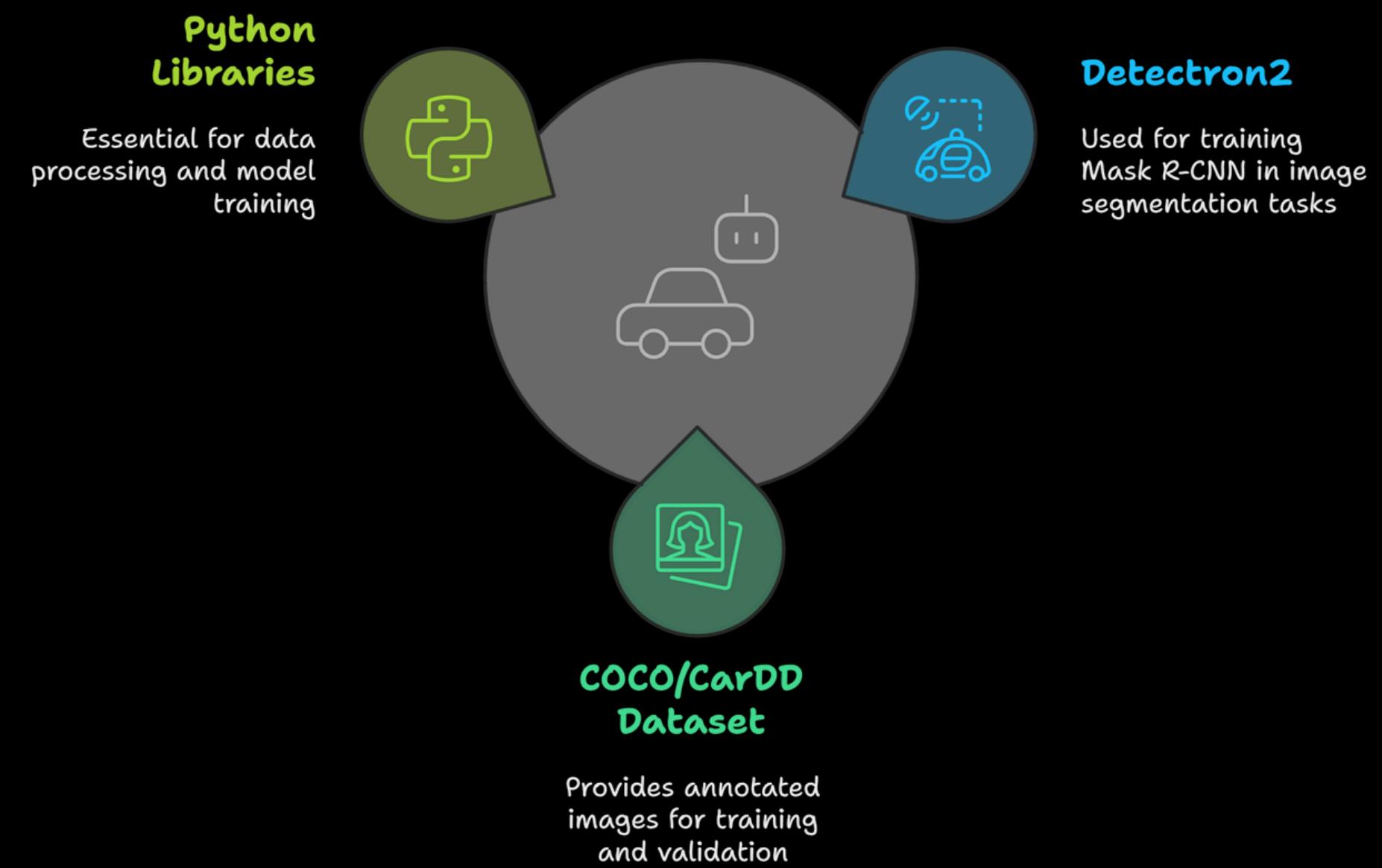
MODEL-ARCHITECTURE:

- Backbone: ResNet-50 + Feature Pyramid Network (FPN).
- ROIAlign for precise mask generation.
-

CUSTOMIZATIONS:

- Added dropout layers to prevent overfitting.
- Adjusted learning rates for better convergence.

TECHNOLOGY STACK



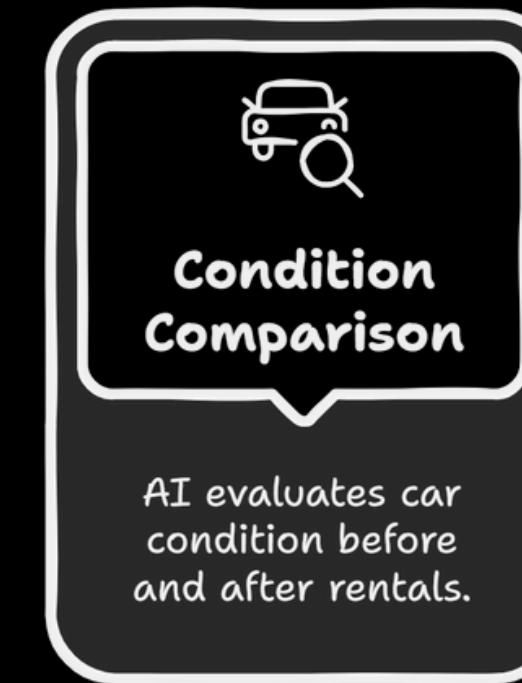
EXAMPLE_USAGE_&_SITUATIONS

📌 AUTOMATED INSURANCE CLAIM PROCESSING



- 01 Customer Uploads Photos
- 02 AI Detects Damage
- 03 Cost Estimation
- 04 Instant Claim Processing

📌 CAR RENTAL DAMAGE ASSESSMENT



Condition Comparison

AI evaluates car condition before and after rentals.



Damage Detection

Identifies new damages and estimates repair costs.



Fair Assessments

Provides unbiased evaluations for companies and customers.

? WHY DOES THIS MATTER?

- ✓ Faster & more accurate claims → Reduces delays for customers.
 - ✓ Prevents fraud → Ensures only genuine damage is charged.
 - ✓ Automates manual tasks → Saves time & operational costs.
- 🚀 Revolutionizing vehicle damage assessment with AI!

TRAINING DETAILS

MODEL TRAINING:

- Dataset: Damaged car images with annotations (split: 2819 train, 813 val).
- Architecture: Mask R-CNN with ResNet-50 + FPN.
- Training Time: ~6 hours on GPU (Google Colab Pro).
- Optimization: Adam optimizer, Learning Rate = 0.001 (adjusted during training).
- Data Augmentation: Random flips, brightness adjustment, scaling.

TESTING STRATEGY

Testing Conducted On:

- 377 unseen images (test set).
- Includes all types of damages: dents, scratches, cracks.

Testing Environment:

- Evaluated using model checkpoints with best validation performance.
- Real-world test: Also tried on 10 unlabelled car images found online to assess generalizability.

EVALUATION METRICS

- For Damage Detection (Mask R-CNN):
- IoU (Intersection over Union): Mean IoU = 0.78
- Precision: 84%
- Recall: 80%
- F1-score: 82%
- For Cost Prediction (Regression):
- Mean Absolute Error (MAE): ₹320
- R² Score: 0.82

FUTURE SCOPE

- ADD SUPPORT FOR MORE VEHICLE PARTS AND 360° DAMAGE ASSESSMENT.
- INTEGRATE WITH MOBILE APPS FOR INSTANT DAMAGE ANALYSIS.
- USE DIVERSE DATASETS TO IMPROVE PERFORMANCE ACROSS VEHICLE TYPES AND ENVIRONMENTS.
- INCORPORATE NLP TO PROCESS TEXTUAL ACCIDENT DESCRIPTIONS FOR BETTER CLAIM ESTIMATION.

BIBLIOGRAPHY

1. HE, K., GKIOXARI, G., DOLLÁR, P., & GIRSHICK, R. (2017). MASK R-CNN. ICCV.
2. SAHA, S., ET AL. (2020). AUTOMATED DAMAGE DETECTION ON CARS USING DEEP LEARNING. ARXIV PREPRINT.
3. COCO DATASET: [HTTPS://COCODATASET.ORG/](https://cocodataset.org/)
4. KERAS DOCUMENTATION - [HTTPS://KERAS.IO/](https://keras.io/)
5. SCIKIT-LEARN REGRESSION METRICS - [HTTPS://SCIKIT-LEARN.ORG/](https://scikit-learn.org/)

RESULTS

