Report on an AI and Algorithmic Pothole Solution

C.R.A.T.E.R: Cognitive Roadway Anomaly Tracking and Evaluation Robot

William Wu[1] and Pranav Gangavarapu[1]

[1]Rancho Cucamonga High School, USA

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Senior

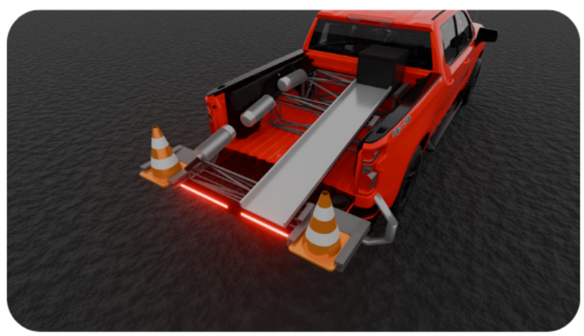
Team C.R.A.T.E.R.

An 11th grader at Rancho Cucamonga High School, William Wu is skilled in robotic hardware, artificial intelligence, and software design.

3-time international WRO qualifier and 2nd place international finalist in 2024, William is exceptional in robotics and computer science.

A 11th grader at Rancho Cucamonga High School, Pranav Gangavarapu excels in data analysis, artificial intelligence, and 3D modeling.

Pranav is highly skilled in computer science and has gotten a perfect score on the PSAT.



Executive Summary

Potholes pose a widespread and persistent threat to public safety and urban infrastructure. In response, we introduce C.R.A.T.E.R., an AI-enabled system that detects, evaluates, and autonomously repairs potholes. Our platform combines real-time AI inference, tracking, and a robotic repair unit mountable on standard pickup trucks. This end-to-end solution enables cost-effective, efficient pothole management by integrating data analysis, interactive visualization, and automated physical response. Our mission is to streamline city maintenance workflows, reduce vehicle damage, and improve roadway safety.

1 Introduction

1.1 Inspirations

This project was inspired by personal experiences and a shared desire to improve public infrastructure, aligned with the WRO2025 theme on sustainable city development. Encounters with road damage during daily commutes and personal issues underscored the urgency of this issue. We identified a significant opportunity to leverage the growing field of AI and robotics to develop a scalable, cost-effective pothole mitigation system.

1.2 The Problem

Potholes have been a persistent threat to roadway integrity and vehicular safety since the widespread adoption of paved roads. They arise from a variety of causes, including fluctuating temperatures, excessive moisture, and broader impacts from climate change [Hira, 2017].

In the United States alone, pothole-related damages are estimated to cost $26.5 billion annually [Arthur, 2024, Edmonds, 2022]. Furthermore, potholes contribute to approximately 30% of roadway fatalities: roughly 10,000 lives lost per year [Arthur, 2024]. These alarming statistics highlight the urgency of developing innovative, efficient solutions beyond current maintenance practices.

2 Project Description

2.1 Overview and Project Evolution

The C.R.A.T.E.R. system is a comprehensive, 3 phase solution designed to address the pothole crisis at scale. Our approach consists of:

1. **Detection:** A compact, AI-powered detection unit that can be mounted on any vehicle (like a dashcam) to identify potholes in real time during routine drives.
2. **Analysis:** Efficient processing of pothole data using clustering algorithms and heat maps to prioritize high-risk areas.
3. **Repair:** A cost-effective robotic unit mountable on standard pickup trucks that autonomously dispenses cold asphalt to repair potholes based on priority data. Projected to reduce pothole costs by up to 90%.

Figure 1 shows the user-friendly dashboard we developed for city planners and our pothole fixers alike to interact with real-time data, visualize hotspots, and coordinate efficient repairs.

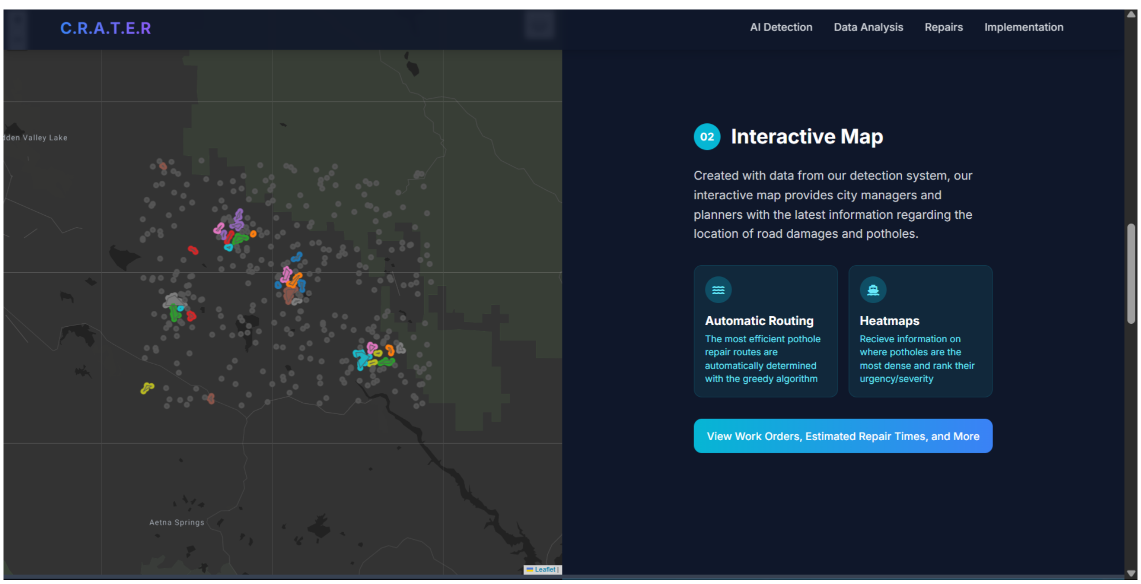


FIGURE 1 Interactive Website for Data Analysis

The timeline for our project developement is given below in Table 1.

Table 1 Project Evolution

March	Project idea concevied for general pothole detection and repair using AI and robotics
April	Pothole detector AI model trained with high accuracy; conjectured mechanisms for pothole repair using cold asphalt
May	Robotic prototype built using mechanical components; AI model transported to raspberry pi and configured to run at relatively high fps; data analysis idea conceived
June	Robotic prototype tested and refined; initial data analysis algorithms implemented using DBSCAN
July	3D modeling for robotic repair mechanism for real-life system; added heatmap analysis to pothole data
August	Website designed and deployed for data analysis and visualization
September	Early dashcam model conception for AI detection model
October	3D printed prototype dashcam casing model; designing dashcam system

2.2 Technical Aspects

2.2.1 Mechanical Construction

Our prototype version for the pothole fixer is built using a mix of off-the-shelf components and 3D printed hardware. For the robotic prototype, it includes a Raspberry Pi 4B, GPS module, Logitech webcam, an FTC robotic frame, servos, ESCs, and custom-designed 3D-printed parts. The detection component on the other hand only requires a computer chip, GPS, and camera. Each component contributes to an integrated system capable of real-time detection and physical pothole repair.

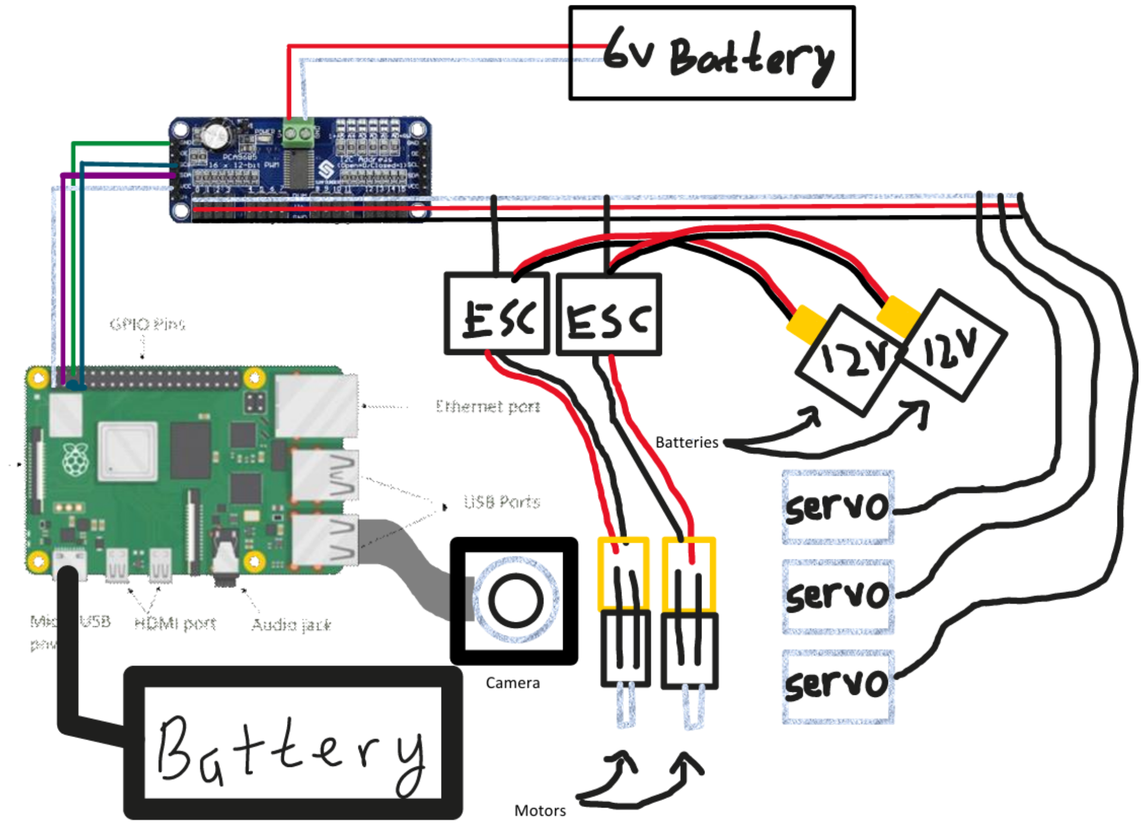


FIGURE 2 Wiring Diagram

Raspberry Pi 4B: Acts as the central processing unit for running the AI model and interacting with connected sensors and motors. A Jetson Nano is under consideration for future upgrades due to its superior AI processing capabilities.

Webcam: Provides high-resolution real-time images of the road surface, enabling pothole detection through the Raspberry Pi.

GPS Module: Logs precise coordinates for each detected pothole, enabling accurate mapping and tracking over time.

Robotic Frame: Constructed from standardized FTC components, this frame supports the deployment of servos and motors required for asphalt dispensing and smoothing. As this is only for the prototype, in real life we would most likely used custom welded metal.

Interfacing and Signal Conversion: Off-the-shelf motors and servos required adaptation for compatibility with the Raspberry Pi. This was achieved using a 15A motor controller and a PWM Servo Hat, allowing translation of BEC signals into PWM instructions. In other words, we used electronic speed controllers to adapt electrical signals.

Custom 3D-Printed Components: To bridge limitations of off-the-shelf hardware, we designed and printed specialized parts using Blender. These components were tailored using physics-based calculations to ensure optimal fit and performance in the repair process. An example of this is shown in figure 4

The completed robotic unit is mountable on common pickup trucks, enabling flexible deployment across different cities. As far as the prototype goes, we have already invented a system to dispense asphalt and smooth it out.

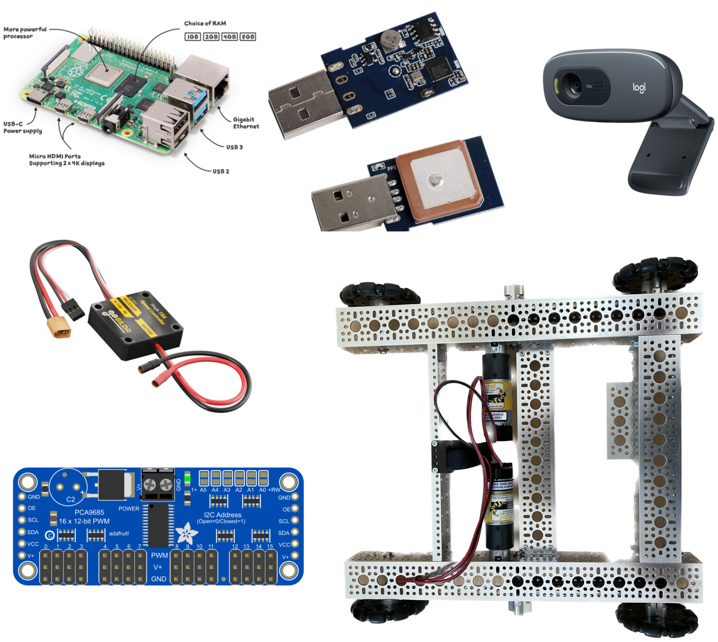


FIGURE 3 System parts

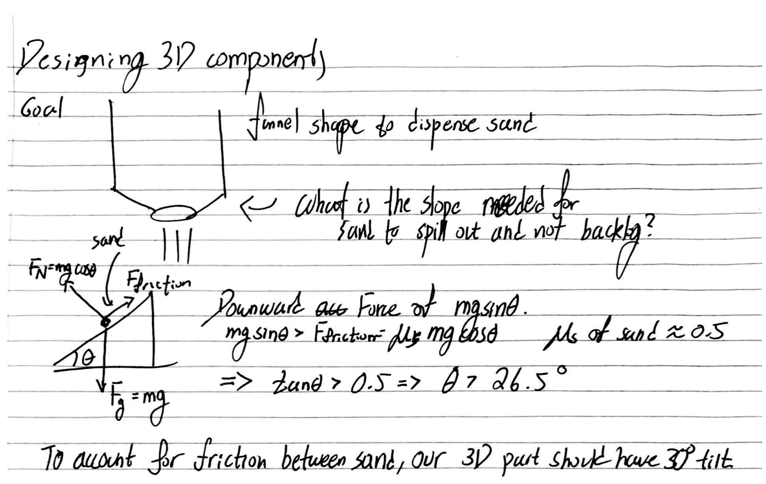


FIGURE 4 Engineering Calculations for 3D Model

To show the viability of our repair design, we modeled and animated the truck mounted pothole repair system using Blender (Figure 5).

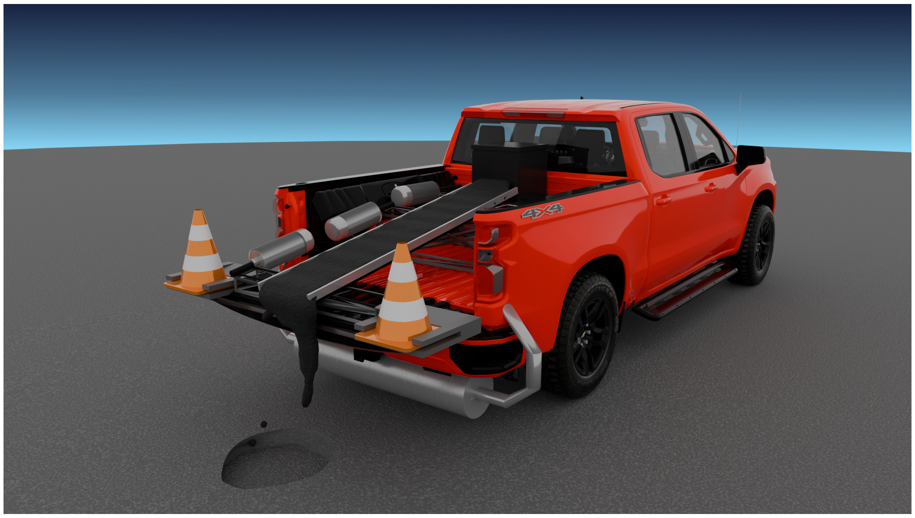


FIGURE 5 3D Model of Truck-Mounted Repair System

In addition, we also designed and 3D printed a dashcam system for the AI detection system (Figure 6). This prototype dashcam is designed to host a Raspberry Pi, camera, GPS, and buttons for power and reset. The casing is designed to be mounted on a car windsheild.

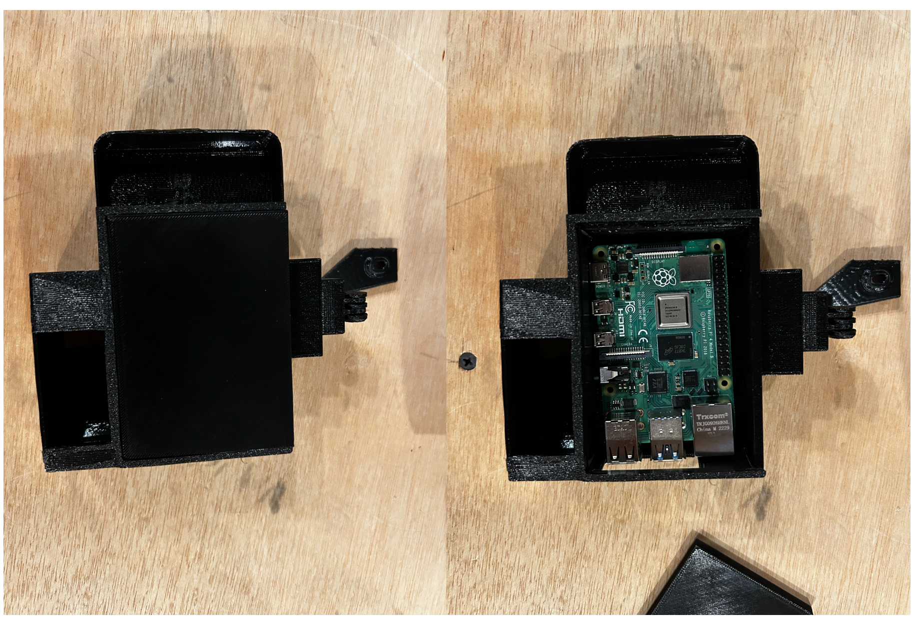


FIGURE 6 3D Model of Dashcam System

2.2.2 Software Construction

AI Model: The cornerstone of our detection system is a custom-trained object detection model using YOLOv11. We utilized Roboflow to source and annotate approximately 10,000 images of potholes (Figure 7). They can then be used to train our YOLOv11 nano model, chosen for its high speed and low memory: ideal for deployment on lightweight computing platforms such as our Raspberry Pi.

FIGURE 7 Annotating Images For Training

Training Details: The YOLOv11 nano model was trained for 100 epochs. On a CPU, each epoch took roughly 45 minutes; GPU acceleration reduced this to under 1 minute per epoch. GPU usage enabled full training completion in approximately two hours, significantly accelerating development.

Data Analysis: After pothole data is collected and logged, it is processed using the following methods:

1. **Heatmap Clustering:** We generate spatial heatmaps to identify dense clusters of potholes. This helps our vehicles and city planners plan for fixing.
2. **DBSCAN:** A density-based clustering algorithm that detects natural groupings of potholes, accommodating irregular geographical distributions.
3. **Greedy Algorithm:** Within each cluster, a greedy algorithm identifies efficient traversal paths, reducing fuel consumption and labor

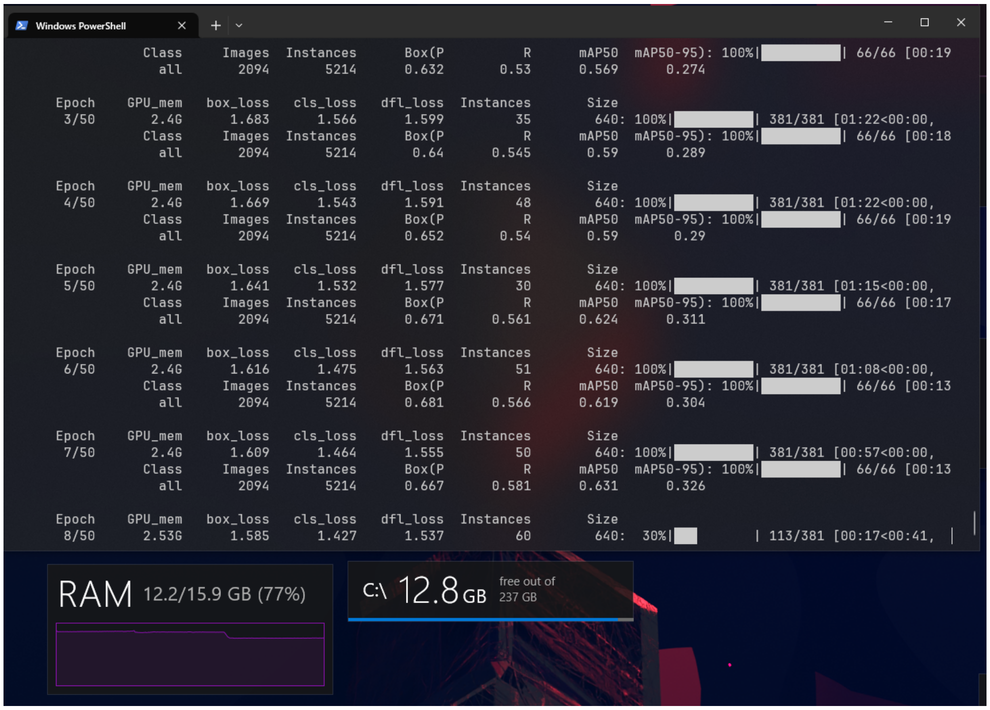


FIGURE 8 Training the AI Model

hours during repairs. Note: this is a non-optimal fix to the traveling salesman program but drastically reduces complexity from $\mathcal{O}(n!) \rightarrow \mathcal{O}(n^2 \log_2 n)$.

Dashboard and Alerts: Once all of the computation is completed, we still need to design a way to access and broadcast all this data. The processed data is visualized via a custom-built website. This dashboard enables city planners to view pothole locations, cluster rankings, and fixing time. The platform also supports alerting for high-urgency zones, promoting timely responses. The website we developed can be found here https://titanthemoon.github.io/CRATER-Web/.

2.2.3 System Integration Calculations

During the Panama Open internationals, the future innovators head elementary judge brought up a very concerning point about the project: whether the repair system could really be feasible to implement in real life. Many asphalt containing vehicles need special reinforcement in order to handle the weight of the asphalt, and implementing an asphalt box directly on the back of a pickup truck raises some concerns. Troubled by this, we thoroughly investigated how weight structures affect the suspending axles, frame bending, and how vehicular acceleration affects truck ca-

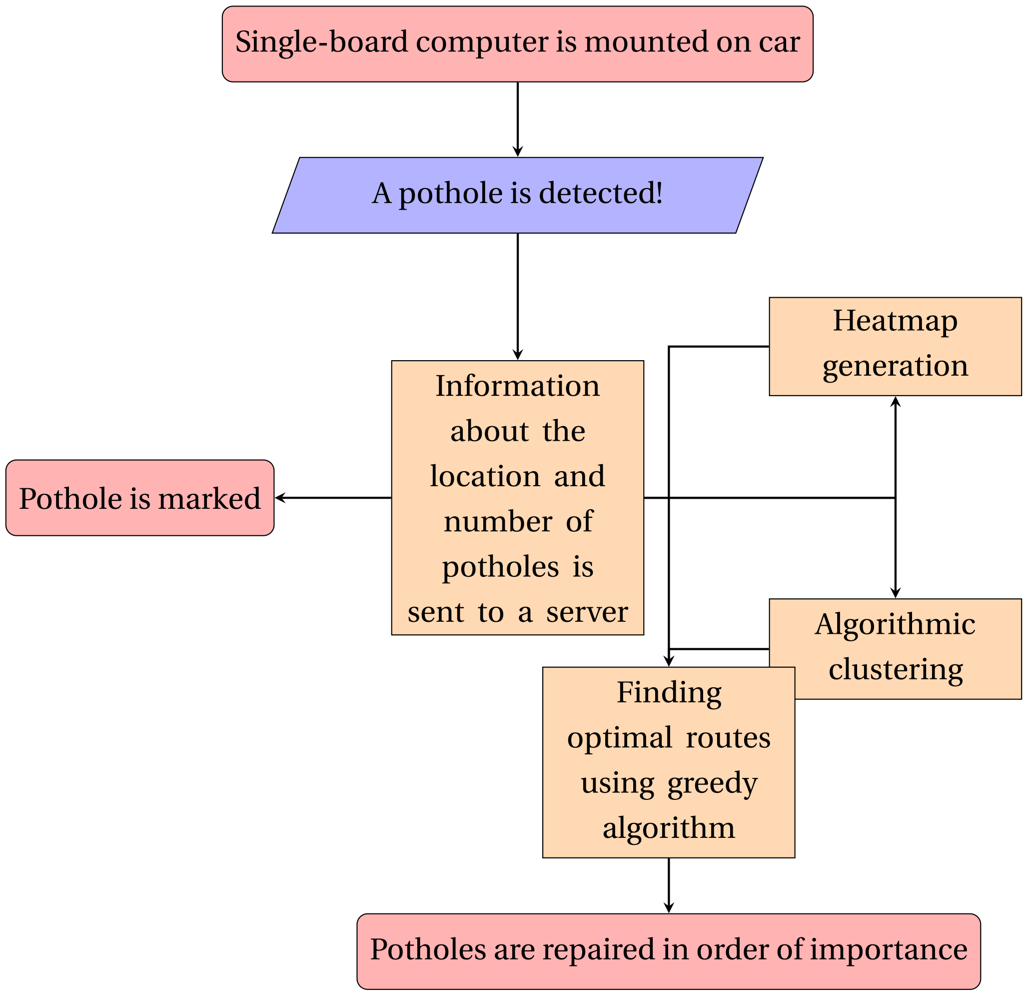


FIGURE 9 Software Flow Chart

pacity. It is to be noted that all of our calculations are based on a standard Ford f-150 XLT SWB truck. The specs can be found in [caranddriver.com, 2025, carexpert.com, 2024].

The following calculation (Figure 10) is for whether the suspending axles of the truck can handle the weight of the asphalt box. Assuming a $0.5 \times 0.4 \times 1.5$ m^3 asphalt container with asphalt of density 2210 kg/m^3, and assuming the weight distribution of the truck itself on the front and back axles is a 60 : 40 ratio with a 1991 kg truck, we get the following estimates. It can be shown that there is over 300 kg of leeway on both axles, enough to carry the weight of the rest of the robotic unit. Thus, we can conclude that the weight of the asphalt container will not require any extra reinforcement on vehicle axles.

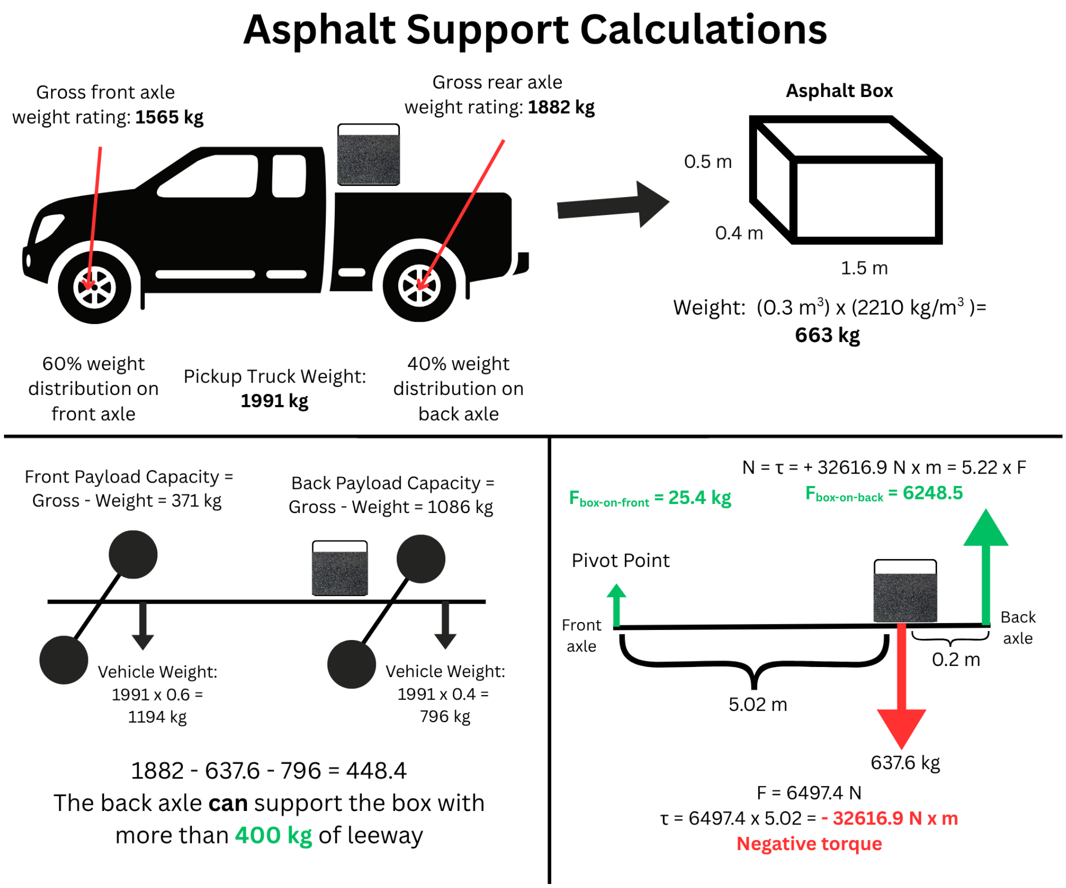


FIGURE 10 Training the AI Model

The following calculations details the stress analysis of the asphalt, truck cab, and the bed frame. It can be concluded that even under severe conditions, the weight of the asphalt is nowhere near enought to cause significant bending on the steel frames of the pickup truck.

Truck Cab Stress Analysis: Research shows that standard pickup trucks are made of high strength steel with around 250 MPa of yield strength [Materials, 2012]. The horizontal stress on the cab of the truck head can be calculated similarly to (Equation 2). We can see that the 8.7 kPa of stress on the truck cab is much less than the yield strength of steel, so the asphalt weight will not affect the cab.

Asphalt Stress Analysis: The weight of the asphalt is 663 kg or 6505 N. To get the static normal stress on the bottom of the asphalt box, which is $1.5 \times 0.4 = 0.6$ m^2, we use

$$\sigma_{normal} = \frac{F_{vertical}}{A} = \frac{6505}{0.6} = 10.8 \text{ kPa}. \tag{1}$$

This pressure is significantly lower than the compressive strength of typical asphalt concrete, which ranges anywhere from 2 MPa to 50 MPa [pavementinteractive.org, Wang et al., 2024]. In addition, assuming a worst case acceleration of 1g= 9.81 m/s^2, asphalt would experience a horizontal sheer stress on the side of the box, which measures $1.5 \times 0.5 = 0.75$ m^2. Then,

$$\tau_{h\_sheer} = \frac{F_{horizontal}}{A} = \frac{663 \times 9.81}{0.75} = 8.7 \text{ kPa}. \tag{2}$$

The horizontal sheer stress is also significantly lower than the tensile strength of asphalt, which is approximately 1 MPa [Khosla and Harvey]. Thus, it is safe to assume that the weight and conditions of the asphalt will not cause deformation to the asphalt itself.

Truck Frame Stress Analysis: Finally, it suffices to show that the concentrated weight of the asphalt will not bend the frame of the vehicle. The weight of the asphlt will distribute to 3252.5 N for each of frame (left and right). From the Ford f-150 specs, we get that the frame length is aprpoximately 1.7 m. We can model the frame as a straight beam and estimate the worst case scenario where the weight is directly concentrated in the middle of the frame. The bending moment is calculated as

$$M = \frac{PL}{4} = \frac{3252.5 \times 1.7}{4} = 1382 \text{ N} \tag{3}$$

The section modulus for a heavy duty truck is around 2.08×10^{-4} m^3 [allstatetrucks.com, 2018], so we can estimate in the worst case that a pickup truck has a section modulus of 1×10^{-5} m^3. Then, calculating the bending stress,

$$\sigma_b = \frac{M}{S} = 138.2 \text{ MPa} \tag{4}$$

gives us that even in the worst case scenario, bending stress is still much less than the 250 MPa yield of high strength steel.

Finally, we will update and detail exact mechanical blueprints and further calculations in our GitHub repo [william11074].

2.3 Development Process and Challenges

2.3.1 Hardware Integration

Integrating off-the-shelf components posed mechanical and electrical compatibility challenges. For instance, connecting FTC motors with the Raspberry Pi required several signal converters and GPIO programming (In this case, we used a ESC connected to a PWM driver that is then connected to the Pi's GPIO pins). Additionally, we encountered issues with dispensing asphalt effectively, ultimately leading us to engineer custom 3D-printed parts to fit our needs.

2.3.2 Computation Power Constraints

Throughout the project development phase, we were consistently met with computation issues. This was mostly due to lack of computation power and overly complicated software.

1. **Model Optimization:** Our initial YOLO model (medium size) caused unacceptable performance bottlenecks. Switching to a nano variant significantly improved inference speed without compromising accuracy.
2. **Low FPS on Raspberry Pi:** Even with the smaller model, frame rates were around 1 FPS. By implementing multithreading (aka parallel processing), we increased output to approximately 15 FPS.
3. **Training Time:** CPU-based model training was inefficient, prompting a swap to GPU-based pipelines with CUDA support, improving iteration speeds by ~45x.

2.3.3 Scaling Problem

Our early vision of a single AI-detection-and-repair robot was not viable at scale. Instead, we modularize the solution into separate detection and repair components. The detection unit can be mass-deployed on public and municipal vehicles. The repair unit, meanwhile, remains dedicated to prioritized repairs: allowing a decentralized and scalable deployment strategy.

2.3.4 Other Challenges

One of the most critical issues we faced occurred just before the U.S. Nationals. The robot suddenly shut down, and to our shock, some of the wires even began to melt. We attempted several lots of debugging methodologies.

1. **Testing the Batteries:** Initially we thought that the batteries were broken so we tried to charge them and plug them back in. It turned out that both of our batteries were fried and that when we plugged them in, the wires started burning up.
2. **Grounding:** The fact that the wires heated and the batteries were fried told us that the ground was potentially broken. We then got a multimeter to test the ground between the batteries, but they seemed to all be connected.
3. **Broken PWM Driver:** Next, we replaced the PWM driver and tested it with a spare servo. Surprisingly, it worked. This led us to believe the original PWM driver was defective, so we replaced it. Unfortunately, the robot still didn't function, and we were left without a clear direction.
4. **Broken ESC:** After hours of testing and panicking, it finally hit us that maybe one of the parts connected to the PWM driver were broken. We started testing each of the grounds until we actually discovered that one of ESCs was broken and actually caused the whole problem!

Now that we found out the ESC was broken, we needed to quickly solve the problem before nationals. As shipping would take too long, we had to confront the fact that we had just one motor to work with. Having iterating through a few prototypes, we came to the idea of connecting both motors through a shaft so that at least the robot can move during the competition. Although this experience was stressful and frustrating, it ultimately taught us valuable lessons in resilience, problem solving, and creative engineering under pressure.

2.4 Competitive Analysis

While C.R.A.T.E.R. is a completely new and novel concept to mitigate the pothole crisis, there are a few existing solutions that address parts of the problem. These include pothole repair vehicles and AI-based detection systems. Major competitors in this market include the Python 5000

Pothole Patcher and Cityrover's edge detection model. Through technical and cost analysis (see Table 2), we conclude that C.R.A.T.E.R. is a much better solution than existing alternatives.

TABLE 2 Competitor Analysis

Feature	C.R.A.T.E.R.	Cityrover	Python 5000
Detection Method	High accuracy AI, Real-Time	Basic detection model, undisclosed accuracy	no detection
Repair Mechanism	Autonomous Robotic Unit	no repair	Manual repair, requires employee training
Cost Efficiency	Low-Cost Components (See 3.2.2)	Undisclosed contract costs	Upwards of $500,000 per vehicle
Scalability	Vehicle compatability for both detection and repair	Compatible for detection only	Requires special vehicle
Data Analysis	Advanced Clustering and Heatmaps	Basic Reporting Tools	None
User Interface	Interactive Dashboard	Limited or No Interface	Limited or No Interface

3 Beyond the Competition

3.1 Social Impact & Innovation

3.1.1 Social Impact

- **Safety Improvements:** Our system directly reduces injuries and fatalities caused by potholes on roadways.
- **Municipal Efficiency:** Besides fixing potholes ourselves, the system provides city planners with insights and automated logistics for road repair prioritization.
- **Affordability:** Competing solutions often require custom vehicles costing 6+ figures. Our modular platform is significantly more accessible, especially in underdeveloped regions.

3.1.2 Innovation Highlights

- **CNN-based Real Time Detection:** A practical application of AI inference in urban planning.
- **Custom Hardware:** We designed custom mechanical components to enhance system integration.

- **Crowdsourced Detection Model:** Our detection system can be mounted on any vehicle, enabling distributed data collection city-wide.
- **Two-Phase Architecture:** Separating detection and repair maximizes efficiency and cost-effectiveness.

3.1.3 Potential Drawbacks

- **Weather Limitations:** The robotic repair unit currently uses cold asphalt, which may not be effective in extreme weather conditions. Future iterations could explore heated asphalt or alternative materials.
- **AI Misidentification:** While our model is highly accurate, there is still a risk of false positives/negatives. Ongoing training and validation are essential to maintain reliability.
- **Initial Deployment Costs:** Although cost-effective in the long run, initial setup and deployment may require upfront investment from municipalities.
- **Self Driving Integration:** Since the goal for the autonomous repair robot is to have zero human intervention, a self-driving car solution is required. Deployment of automated vehicles could potentially be haphazard to other drivers if not engineered properly.

In summary, our project not only leverages cutting-edge technology to tackle a pressing safety issue, but also improves current logistical systems. Through innovative design and persistent refinement, we strive to create a robust solution that can be adopted globally to enhance roadway safety.

3.2 The Business Model

3.2.1 Revenue Stream

The demand for smart infrastructure maintenance solutions is rapidly growing. Our target audience includes municipal governments, insurance companies, and transportation safety organizations.

- $26.5B in annual damage underscores urgent demand.
- Government agencies seek efficient, scalable safety technologies.
- Potential for international adoption in high-traffic urban zones.

3.2.2 Cost Analysis

Estimated Costs:

- Detection unit (camera + chip): $100 (can be reduced via manufacturing partnerships).
- Robotic repair unit (excluding cost of pickup truck): $6,000 per truck.
- Asphalt + Fuel: $52 per pothole.

Maintenance: Cities and counties often have dedicated maintenance crews for their fleet vehicles. To estimate the maintenance costs of our pothole repair unit, we compared it to the monthly maintenance cost of a typical construction vehicle, which is approximately $300. Assuming one repair unit addresses five potholes per day, this results in an estimated maintenance cost of about $2 per pothole. Notably, this cost is relatively minor compared to the overall expenses of asphalt and fuel, making it a manageable and cost-effective component of the total operating budget.

3.2.3 Economic Benefits

1. **Cost Savings:** Fixing potholes can save billions in damages per year. In our local city of Rancho Cucamonga, public works department told us they fill roughly 6000 potholes per year. With our system, we can save the city around $3,000,000.
2. **Resource Optimization:** The use of our system reduces manual labor, allowing for more efficient resource allocation.
3. **Insurance Reduction:** Effective pothole management can lower the risks of driving, leading to lower insurance rates. This benefits civilians.
4. **Investment Opportunities** As our technology continues to expand and grow, it opens up investment opportunities. This helps create more economic growth.

3.2.4 Feasibility

- **Technologically Viable:** Prototypes are functional and are ready to scale up to real-world models.
- **Scalable:** Units can be mass-produced and deployed on existing vehicles.

- **Financial Backup:** Powerful idea leads to potential grants and funding.
- **Collaborative Potential:** Government and enterprise partnerships will help accelerate adoption.

3.2.5 Key Resources and Partners

It is highly likely that the majority of our collaborations will be with local counties and cities. Municipalities often offer third-party contracts, creating a clear pathway for partnership. For instance, during discussions with the Public Works Department of Rancho Cucamonga, they confirmed that they regularly outsource certain projects; further validating the feasibility of this approach. Partnering with cities would also allow for permits to work on city roads.

In addition to public partnerships, we aim to secure investment funding to support implementation and scale. Once partnered with a city, the key requirements for success include effective training for municipal workers, proper permits for roadway work, and well-established communication channels between teams.

Given these factors, we believe our project is not only practical but highly implementable within existing municipal systems.

3.3 Next Steps

Future development will focus on:

- Enhancing AI with satellite and night-vision capabilities. This may lead to pothole fixing at night, reducing traffic congestion and road blockage.
- Transitioning the web platform to a cloud-based infrastructure, allowing both AI and civilian reports.
- Improving cost and weight efficiency of the robotic unit, allowing for cheaper pothole fixing.
- Pothole volume estimation, lane tracking, and fleet designs as far as technological advancements go.

3.3.1 Appearance Design Optimization

Because we only have a prototype of the actual robotic solution, we need to find a way to turn it into a real product that is attachable to cars.

Our current goals are shifted to actually fool-proofing our real life design and working with real-life materials to build a bigger prototype on one of our own cars.

3.3.2 Potential Objective Shift

While the AI system is mainly trained for pothole detection, the already adaptable design for data storage and collection on vehicles can be modifed to focus on other objectives. For example, we can also train the AI system to detect fading lane lines or broken road signs. In addition, we might also focus on detecting erratic driving and other roadway anomalies. With our CRATER, the possibilities are endless.

4 Conclusion

By leveraging the growing abilities of machine learning models, data processing, algorithmic analysis, and robotic engineering, C.R.A.T.E.R. is a transformative solution to the global pothole crisis. This system detects, analyzes, and autonomously repairs roadway anomalies: improving safety, reducing costs, and enhancing urban infrastructure. Our project stands as a scalable and impactful blueprint for the cities of tomorrow.

C.R.A.T.E.R. | paving the path towards a better future.

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