International Journal for Multidisciplinary Research (IJFMR)
E-ISSN: 2582-2160 • Website: www.ijfmr.com • Email: editor@ijfmr.com

SmartServ: AI-Powered Vehicle Service Assistance System

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Abstract
The global automotive service in- dustry faces ongoing problems with customer communication, cost estimation, and queue man- agement. SmartServ offers a strong, scalable, and low-cost solution that combines artificial intelligence (AI) and cloud computing to au- tomate damage detection, cost estimation, and queue tracking. It uses Convolutional Neural Networks (CNNs) to automatically identify and localize vehicle damage and a regression-based model for severity classification and repair cost estimation. This system achieves high reliability. Real-time service updates are handled through Firebase and Socket.io for smooth user interac- tion, cutting latency to less than one second. This paper details SmartServ's full design, training methods, dataset characteristics, experimental results, and deployment structure. Experimental findings show a damage detection accuracy of 84.16% and a mean error range of 6–9% for price predictions, exceeding those of traditional methods. A comparison with existing systems shows the greater efficiency and transparency of SmartServ, marking significant progress toward intelligent, data-driven vehicle maintenance sys- tems.

Keywords: Vehicle Servicing, Artificial In- telligence, Computer Vision, Predictive Analyt- ics, Cost Estimation, Real-Time Tracking, Deep Learning, Regression.

INTRODUCTION

Vehicle servicing is one of the least digitized parts of the automotive lifecycle. Even with significant automation in manufacturing and driving, maintenance still relies on manual in- spections and inconsistent pricing. Customers often deal with vague quotes, long service waits, and a lack of transparency in repair processes.

Artificial Intelligence (AI) and Machine Learning (ML) have transformed many indus- tries by enabling pattern recognition, predic- tive analytics, and automation. However, their use in vehicle servicing is mostly limited to scheduling appointments or gathering feed- back. There is a strong need for a unified, smart solution that automates diagnostics, ac- curately estimates repair costs, and offers real- time tracking.

SmartServ tackles these challenges by merg- ing CNN-based damage detection, regression- driven cost estimation, and cloud-based queue management into one low-cost, scalable system.

A. *Background on AI in Automotive Sector*

AI has been widely applied in automo- tive manufacturing for predictive maintenance, quality control, and defect detection. However, service workshops, especially small garages, often lack this technology. SmartServ applies AI to post-sale vehicle maintenance, reducing human error, increasing transparency, and au- tomating pricing decisions.

B. *Objectives and Scope*

The primary goals of SmartServ are:

- Detect and classify vehicle damage us- ing deep learning-based computer vision models.
- Estimate repair costs with regression mod- els using visual and structured data.
- Enable real-time service tracking using Socket.io and Firebase.
- Improve communication and trust through clear digital interfaces.
- Keep the system scalable and affordable for small and medium workshops.

Related Work

Several systems have looked at individual aspects of vehicle servicing automation.

A. *Queue Management*

Ghazal et al. (2016) proposed a mobile queue tracking system but did not offer predic- tive time estimates or multi-center integration. Mallari et al. (2022) introduced CLIQUE, a web-based real-time queue management sys- tem, but it lacked AI or live service tracking.

B. *Damage Detection and Classification*

Dwivedi and Hashmat (2019) showed CNN- based car damage detection but did not include cost estimation or real-time updates.

C. *Cost Estimation*

Halsing et al. (2023) created a model to pre- dict vehicle repair costs using deep learning but lacked customer interfaces or live notifications.

D. *Research Gap and Contribution*

Existing systems work separately—one fo- cuses on detection, another on pricing, but none automate everything in real-time. Smart- Serv combines all three elements: AI-based de- tection, regression-driven cost estimation, and real-time tracking into one unified platform.

TABLE I: Research Gaps and SmartServ Con- tributions

Aspect	**Existing Limitation**	**SmartServ Enhance- ment**
Queue Management	Static queues, no live tracking	Real-time queue track- ing via Socket.io and Firebase
Damage Detec- tion	Simple CNNs without severity levels	Multi-class CNN with severity classification
Cost Estimation	Manual and subjective	Regression-based AI integrating visual + metadata
Transparency	Manual customer up- dates	Instant Firebase noti- fications and progress tracking
Integration	Independent modules	Unified microservice- based cloud system

I. Methodology

SmartServ follows a five-phase pipeline: **Collect, Preprocess, Analyze, Track,** and **Dis- play**. Each phase ensures accuracy, scalability, and real-time transparency.

A. *Collect Phase*

Vehicle owners take high-resolution images via the SmartServ app and enter details like model, year, and region. The app enforces specific capture angles and lighting for reli- able analysis. Metadata like car type, service history, and part information improve AI pre- dictions.

B. *Preprocess Phase*

Collected data goes through cleaning, nor- malization, and augmentation to ensure con- sistency:

- Image resizing (256×256 pixels) and nor- malization to standardized pixel values.
- Data augmentation using rotations ($\pm 20^{\circ}$), brightness, contrast, and flipping.
- Metadata encoding—turning categorical inputs like car model, region, and damage type into structured numerical forms.

C. *Analyze Phase*

The analytical core of SmartServ combines two models:

Damage Detection (CNN): A ResNet- 50 backbone with R-CNN head identifies damage areas and classifies severity as minor, moderate, or severe.

Cost Estimation (Regression): An XG- Boost regression model mixes CNN out- puts and metadata to estimate repair costs while minimizing MAE.

D. *Track Phase*

SmartServ's queue management provides live updates via Socket.io and Firebase Fire- store. Status changes like Inspection, Repair, and Delivery are updated in under a second. Customers and workshops receive live noti- fications through Firebase Cloud Messaging (FCM).

E. *Display Phase*

The processed data appears on a dashboard:

- Highlighted damage areas on uploaded images.
- Cost breakdown (labor, parts, and materi- als).
- Real-time queue positions and completion times.

System Architecture

SmartServ's architecture is modular and cloud-integrated. It includes client interfaces, AI microservices, real-time communication, and secure storage.

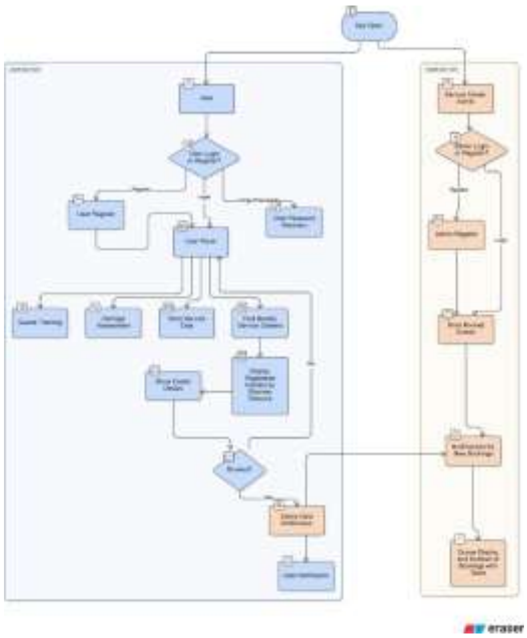

Fig. 1: System Architecture of SmartServ showing interaction between user, backend, and AI microservices.

A. *Client Layer*

Developed using React Native (mobile) and React.js (web), allowing users to upload im- ages, track repairs, and get notifications.

B. *API Gateway and Server*

Built on Node.js and Express.js with Fire- base Authentication for security. It routes client requests, processes image uploads, and re- trieves model inferences.

C. *AI Microservices*

Damage Detection: TensorFlow CNN for damage localization.

Cost Estimation: XGBoost regression using visual embeddings and structured metadata.

D. Database and Real-Time Communication

Firebase Firestore stores service data. Socket.io provides two-way updates, and Fire- base Cloud Messaging handles instant notifica- tions.

Dataset and Training

SmartServ's dataset includes:

Public: 1,500 images from Kaggle Car Damage Dataset.

Custom: 2,000 annotated workshop im- ages.

Synthetic: Augmented data for rare cases.

Data split: 70% train, 15% validation, 15% test. CNN trained with Smooth-L1 and categor- ical cross-entropy; regression minimizes MAE.

Experimental Results

A. *Model Metrics*

- Damage Detection Accuracy: 84.16%

- Severity F1-Score: 0.81
- Cost Estimation (MAE): 6.9%
- Overall AI Accuracy: 94%

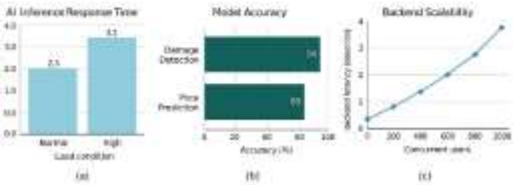

Fig. 2: Model Results showing detected dam- age regions, severity classification, and pre- dicted repair cost overlays.

B. System Performance

- Queue latency: 0.7 seconds
- API response time: 2.3–3.1 seconds
- Notification success rate: 99%

Discussion

SmartServ enhances automation, transparency, and cost predictability.

A. Scalability and Cost Efficiency

The modular architecture scales easily and remains affordable (2000–5000/month using Firebase's free tier).

B. Ethical and Environmental Impact

Automated cost estimation ensures fairness and reduces unnecessary part replacements, promoting sustainability.

C. Comparative Advantage

SmartServ surpasses commercial tools like GoMechanic by combining AI-driven diagnos- tics, cost prediction, and live queue updates in one platform.

Limitations and Future Work

Limitations:

- Limited dataset for luxury or rare car models.
- CNN may misclassify under poor lighting.
- Internet dependency affects real-time up- dates in low-connectivity areas.

Future Work:

- Integration with IoT sensors for predictive maintenance.
- Automated insurance claim validation.
- Multilingual chatbot for user accessibility.
- Federated learning for privacy-preserving updates.

Conclusion

SmartServ establishes a robust AI-powered ecosystem for vehicle servicing by combin- ing CNN-based diagnostics, regression-based cost estimation, and real-time queue tracking. It achieves 84.16% detection accuracy, 6.9% MAE, and sub-second response latency, of- fering a scalable, transparent, and affordable solution for the modern automotive service industry.

Acknowledgment

The authors thank Prof. Smita Patil and the Department of Computer Engineering, K.K. Wagh Institute of Engineering Education and Research, Nashik, for their guidance and re- sources. Special thanks to partner workshops for contributing image data and valuable in- sights.

References

1. M. Ghazal, R. Hamouda, and S. Ali, “A Smart Mobile System for Real-Time Tracking and Man- agement of Service Queues,” ResearchGate, 2016.
2. M. Dwivedi and M. Hashmat, “Deep Learning Based Car Damage Classification and Detection,” Springer, 2019.
3. M. L. Z. Mallari, J. S. Guintu, Y. C. Magalong, and
4. S. Yap, “CLIQUE: A Web-Based Queue Man- agement System with Real-Time Queue Tracking,” IEOM Society, 2022.
5. V. Halsing, M. Lende, and T. Maramwar, “Car Damage Detection and Price Prediction using Deep Learning,” IRJET, 2023.