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DeepClaim: An AI-Driven Framework for Automated Vehicle Damage Severity Assessment and Insurance Cost Estimation

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Abstract: *The process of evaluating vehicle damage and estimating repair costs is a critical component in the automotive and insurance industries. Traditional manual inspection methods are often time-consuming, inconsistent, and susceptible to human error. This study presents DeepClaim, an AI-driven framework designed to automate vehicle damage severity assessment and insurance cost estimation. The proposed system leverages Convolutional Neural Networks (CNNs) for image-based classification of vehicle damage into three categories—minor, moderate, and severe. Using computer vision and deep learning, the system processes vehicle images, predicts severity levels with high accuracy, and provides corresponding cost estimations. A Flask-based web interface enables users to upload damaged vehicle images and receive instant severity predictions along with repair cost insights and insurance recommendations. The framework significantly enhances the efficiency and transparency of insurance claim assessments by minimizing manual intervention and ensuring objective evaluation. Experimental results demonstrate the potential of the system to streamline claim processing, reduce operational costs, and improve customer satisfaction across the automotive and insurance sectors.*

Keywords: *Deep Learning, CNN, Computer Vision, Vehicle Damage Detection, Cost Estimation, Flask Web Application, AI Insurance Automation*

I. INTRODUCTION

Vehicle damage assessment plays a vital role in the automotive repair and insurance industries, where accurate estimation directly impacts claim processing and repair planning. Conventional evaluation methods rely on manual inspections performed by experts, which are often inconsistent, time-intensive, and costly. These limitations lead to delays in claim settlements, disputes over repair costs, and inefficiencies in insurance operations.

With the rapid advancement of Artificial Intelligence (AI) and Deep Learning, automated computer vision systems are increasingly being used to classify and analyze image-based data. Convolutional Neural Networks (CNNs), in particular, have demonstrated outstanding performance in feature extraction and image recognition tasks. Leveraging this capability, *DeepClaim* integrates AI-based vehicle damage assessment and repair cost estimation into a unified framework. The system automates classification of damage severity levels and generates cost estimations to assist both vehicle owners and insurance assessors.

II. PROBLEM STATEMENT

Conventional attendance management practices in educational institutions rely heavily on manual processes such as roll calls or physical signature registers. These methods consume valuable lecture time, introduce human error, and are susceptible to manipulation, including false marking of attendance. Alternative semi-automated systems, such as RFID cards or biometric fingerprint scanners, also face limitations. RFID-based systems may be misused by sharing cards, while fingerprint devices require physical contact, which raises hygiene concerns and may cause delays when handling large groups of students.

This paper presents the design, development, and evaluation of *DeepClaim*, which aims to transform the conventional inspection process into an intelligent, fast, and accurate digital solution.

III. OBJECTIVES OF THE STUDY

The main objective of this study is to design and develop an AI-driven framework capable of automating vehicle damage severity assessment and repair cost estimation using deep learning techniques. The system aims to overcome the limitations of traditional manual inspection methods by introducing a fast, reliable, and objective solution for the automotive and insurance industries.

It focuses on employing Convolutional Neural Networks (CNNs) to classify vehicle damages into predefined categories—minor, moderate, and severe—based on image inputs. In addition to classification, the framework integrates an automated cost estimation mechanism that provides approximate repair expenses according to the severity of the damage.

The project also emphasizes user accessibility through a Flask-based web interface that enables users to upload vehicle images and instantly receive assessment results along with insurance recommendations. Furthermore, the study seeks to ensure transparency, consistency, and scalability by reducing human bias, improving processing speed, and enabling integration with cloud and mobile platforms for future enhancements.

IV. METHODOLOGY

The methodology adopted for the *DeepClaim* framework integrates computer vision, deep learning, and web technologies to automate vehicle damage evaluation and cost estimation. The process begins with dataset collection, where a labeled dataset of vehicle images is gathered from reliable sources such as Kaggle, categorized into three classes—minor, moderate, and severe damage. Next, image preprocessing is performed using OpenCV techniques such as resizing, normalization, and noise reduction to ensure consistent input quality for the model. A Convolutional Neural Network (CNN) is then trained using TensorFlow and Keras to automatically extract features and classify the damage severity from the processed images.

Once the model is trained, it is deployed into a Flask-based web interface where users can upload damaged vehicle images and instantly receive predictions along with estimated repair costs and insurance recommendations. Finally, the system generates a downloadable PDF report containing all results, ensuring ease of access and transparency. This structured methodology ensures that the system operates efficiently, accurately, and reliably in real-world insurance and automotive scenarios.

V. LITERATURE SURVEY

Automated vehicle damage detection and assessment have emerged as important research areas in recent years, driven by the growing demand for faster and more accurate claim processing in the automobile insurance industry. Early studies primarily focused on manual inspection methods or basic machine learning techniques that relied on handcrafted features such as color, texture, and shape. While these approaches provided initial automation, they lacked precision and robustness under varying lighting, viewing angles, and vehicle types. Researchers soon began exploring deep learning methods, particularly Convolutional Neural Networks (CNNs), which demonstrated superior performance in image classification and pattern recognition. Several studies employed transfer learning using pretrained models like VGG16, ResNet50, and InceptionV3 to classify vehicle damage images with high accuracy. Others integrated object detection algorithms such as YOLO and Faster R-CNN to locate damaged regions and improve interpretability, proving that deep learning could effectively outperform traditional computer vision approaches in real-world scenarios.

With continued advancements in AI, more recent research has focused on combining damage classification with repair cost estimation to support the insurance claim process. Studies by various researchers have introduced hybrid models integrating CNN and regression techniques to estimate damage severity and approximate repair costs. Some works also highlight the use of image segmentation networks such as Mask R-CNN to identify damaged parts more precisely, improving the reliability of cost predictions. However, despite these developments, most existing systems remain limited to either classification or detection tasks without providing a complete end-to-end solution. The *DeepClaim* framework bridges this gap by integrating automated damage classification, cost estimation, and insurance recommendations within a unified, web-based platform. This approach enhances efficiency, reduces manual intervention, and offers a practical, scalable solution for real-world automotive and insurance applications.

VI. EXISTING SYSTEM AND PROPOSED SYSTEM

A. EXISTING SYSTEM

Student attendance systems rely heavily on manual roll-call or biometric devices such as fingerprint scanners and RFID cards. In the existing vehicle damage assessment process, evaluation and cost estimation are performed manually by insurance assessors or vehicle experts. This traditional approach heavily depends on human judgment, experience, and visual inspection, which often leads to inconsistencies and delays in claim processing. Manual inspections are time-consuming, prone to human error, and may vary from one evaluator to another, resulting in disputes between customers and insurers. Additionally, the process requires physical access to the damaged vehicle, making it inefficient and costly, especially when handling a large number of claims.

Some existing digital tools use basic image analysis or rule-based systems, but these lack the capability to adapt to diverse damage patterns and environmental variations. Consequently, the traditional systems fail to deliver the speed, accuracy, and transparency required in modern insurance operations.

B. PROPOSED SYSTEM

The proposed *DeepClaim* system introduces an AI-driven, automated framework that leverages deep learning and computer vision to overcome the limitations of manual assessment. The model utilizes Convolutional Neural Networks (CNNs) to classify vehicle damage severity into three categories—minor, moderate, and severe—based on uploaded images. It integrates an intelligent cost estimation module that predicts approximate repair expenses according to the severity level. A Flask-based web interface enables users to upload images, view real-time results, and download detailed reports containing damage classification, estimated cost, and insurance recommendations. By automating the entire evaluation process, the proposed system ensures higher accuracy, consistency, and speed, while significantly reducing human intervention and operational costs. Overall, *DeepClaim* provides a scalable and transparent solution that can revolutionize vehicle damage assessment and insurance claim management.

VII. FEASIBILITY STUDY

A. Economic Feasibility

The *DeepClaim* system is highly cost-effective as it uses open-source tools like Python, TensorFlow, and Flask. It does not require expensive hardware or software licenses, and the entire setup can run efficiently on standard computer systems, making it affordable for insurance companies and repair centres.

B. Operational Feasibility

The system is easy to operate with a simple web interface that allows users to upload images and receive instant results. It requires minimal technical knowledge, integrates smoothly into existing workflows, and enhances productivity without additional training or manual effort.

C. Technical Feasibility

Built using CNN, OpenCV, and Flask, the project ensures high performance and scalability. It runs efficiently on commonly available systems and can be easily upgraded with cloud or mobile integration, ensuring technical reliability and long-term adaptability.

D. Legal And Ethical Feasibility

The system adheres to privacy and ethical guidelines by processing only vehicle images without storing personal data. It ensures transparency and fairness in AI-driven predictions, promoting responsible and lawful use of artificial intelligence in the insurance domain.

VIII. TOOLS AND TECHNOLOGIES USED

A. Programming Language

The *DeepClaim* system is developed using Python, which offers extensive libraries for machine learning, deep learning, and image processing. Python's simplicity and flexibility make it ideal for developing AI-based applications with efficient data handling and rapid deployment capabilities.

B. Computer Vision Library

OpenCV (Open-Source Computer Vision Library) is employed for image preprocessing tasks such as resizing, normalization, and noise reduction. It plays a key role in enhancing image quality and preparing data for the deep learning model, ensuring consistency across all image inputs.

C. Deep Learning Framework

TensorFlow and Keras are used to build and train the Convolutional Neural Network (CNN) model for vehicle damage classification. These frameworks provide powerful tools for model design, optimization, and evaluation, ensuring high accuracy and reliability in prediction results.

D. Database/Storage

The application uses MySQL for structured data storage, maintaining user details, prediction logs, and cost estimation records. This database integration ensures secure data management, quick retrieval, and easy scalability for future system enhancements.

E. Hardware

The system runs efficiently on a standard laptop or desktop with moderate specifications (Intel i5 or above, 8GB RAM). No additional hardware is required except for a standard camera when capturing real-time vehicle images, making the setup practical and cost-effective.

F. Supporting Libraries

Additional libraries such as NumPy (for numerical operations), Pandas (for data handling), and Matplotlib (for visualization) are used to enhance data processing and analysis. These libraries improve efficiency in model training, evaluation, and report generation.

IX. SYSTEM DESIGN

A. System Perspective

The proposed *DeepClaim* system is designed as a modular, AI-driven application that integrates multiple components to automate vehicle damage detection and cost estimation. It consists of five primary modules: Image Upload, Preprocessing, CNN-Based Classification, Cost Estimation, and Result Generation. Each module interacts seamlessly to deliver an efficient and accurate workflow. The user interacts with the system through a Flask-based web interface, while the backend handles image processing, prediction, and data storage. The architecture follows a client-server approach, where the client (user browser) uploads vehicle images, and the server processes them using the trained deep learning model to generate results in real time. This modular structure ensures that the system remains scalable, easily upgradable, and adaptable for integration with cloud databases or mobile platforms in the future.

B. Context Diagram

The system context diagram illustrates the interaction between the *DeepClaim* system and external entities. The primary entities involved include:

- 1) User (Vehicle Owner / Insurance Assessor) – uploads images of damaged vehicles and receives damage severity, cost estimation, and insurance recommendations.
- 2) System (DeepClaim Application) – processes uploaded images through the CNN model, classifies damage, and estimates repair costs.
- 3) Database (MySQL) – stores image metadata, prediction results, and cost estimation reports for future retrieval.
- 4) Insurance Platform – optionally receives output reports and cost details to assist in claim verification and processing.

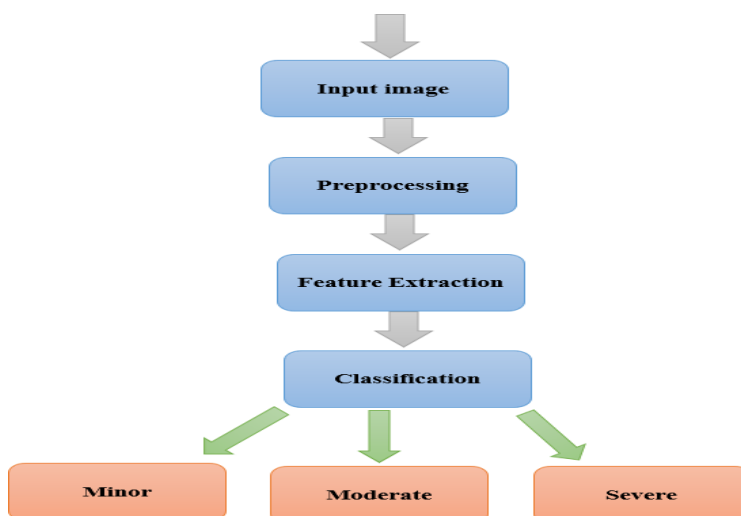


Fig. 1 System Design Diagram of the Proposed Real-Time Student Attendance System

X. USE CASE DIAGRAM

The Use Case Diagram illustrates the functional interaction between the *DeepClaim* system and its external actors. In this framework, there are two primary actors: User (Vehicle Owner or Insurance Assessor) and System Administrator.

- The User interacts with the system by uploading vehicle images, viewing damage severity results, and obtaining cost estimations and insurance recommendations. Their role is primarily to provide input data and review the AI-generated outputs.
- The System Administrator manages backend operations such as dataset updating, model retraining, and maintaining stored reports and user records in the database. They ensure smooth system operation, monitor prediction accuracy, and update cost estimation parameters when needed.

The *DeepClaim* application serves as the system boundary, ensuring that all processes — including image preprocessing, CNN-based classification, cost estimation, and report generation — are executed efficiently. This diagram defines how the actors and the system components interact, mapping every user activity to specific system functionalities before implementation to ensure a smooth and reliable workflow.

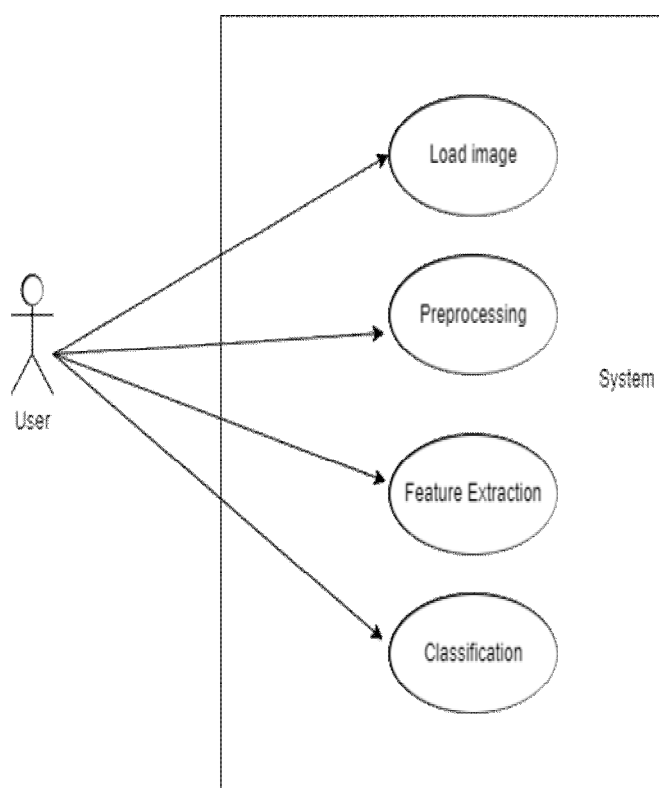


Fig. 2. Use Case Diagram of the Real-Time Student Attendance System

XI. DATA FLOW DIAGRAM (DFD)

The Data Flow Diagram (DFD) illustrates the logical flow of data within the *DeepClaim* system. It shows how information moves between external entities, system processes, and the internal database. The framework ensures seamless communication between modules such as Image Upload, Preprocessing, CNN Classification, Cost Estimation, and Report Generation. Each process works in sequence to deliver accurate and real-time results to the user.

At Level 0 (Context Level), the external entities include the User (Vehicle Owner or Insurance Assessor) who uploads vehicle images and the Insurance Platform that may receive the processed output for claim verification. The user provides input through damaged vehicle images, and the system responds with classified severity levels and estimated costs.

At Level 1, the uploaded image is passed through the Preprocessing Module, where it is resized and enhanced, then sent to the CNN Classification Module for damage severity prediction. The results are forwarded to the Cost Estimation Module, which calculates the approximate repair cost and insurance recommendation. All prediction data and reports are stored in the MySQL Database, from which the admin or user can retrieve past results and reports.

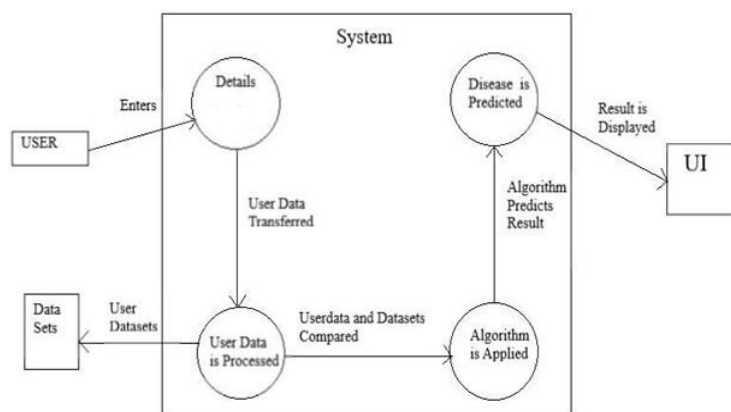


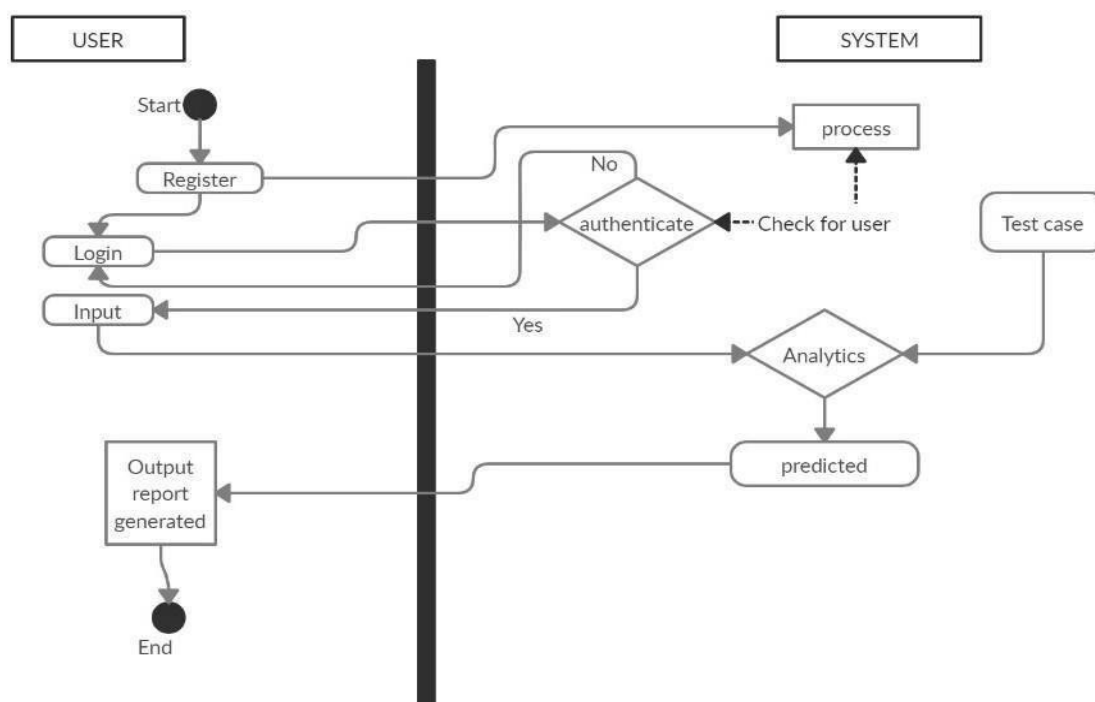
Fig. 3: Data Flow Diagram (DFD) of Real-Time Student Attendance System

XII.ACTIVITY DIAGRAM

The Activity Diagram represents the step-by-step workflow of the *DeepClaim* system, showing how users and system components interact during vehicle damage assessment and cost estimation. It provides a clear understanding of the logical sequence of operations performed from image upload to report generation. The diagram highlights the dynamic behavior of the system and how various modules are connected in the process flow.

The activity begins when the User uploads an image of the damaged vehicle through the Flask-based web interface. The image is first sent to the Preprocessing Module, where it undergoes resizing, normalization, and enhancement using OpenCV techniques. After preprocessing, the image is passed to the CNN Model, which performs feature extraction and classifies the damage as *Minor*, *Moderate*, or *Severe*. The predicted severity level is then forwarded to the Cost Estimation Module, which maps the result to a predefined cost range and generates an estimated repair value. Based on this estimation, the system provides an Insurance Recommendation, advising whether to file a claim or proceed with direct repair. Finally, all results are compiled and displayed to the user, who can choose to download the PDF Report containing the classification, estimated cost, and recommendations.

This activity diagram ensures that each system process is properly aligned, illustrating a smooth flow of control and data from user input to final output, maintaining efficiency, accuracy, and transparency throughout the operation



.Fig. 4: Activity Diagram

XIII. SEQUENCE DIAGRAM

The Sequence Diagram illustrates the dynamic interaction between various components of the *DeepClaim* system over time. It demonstrates how different entities — User, Web Interface, Preprocessing Module, CNN Model, Cost Estimation Module, and Database — communicate with each other to complete the vehicle damage assessment and insurance estimation process efficiently. The diagram helps in understanding the logical flow of actions and responses throughout the system's operation.

1) Image Upload:

- The User initiates the process by uploading a damaged vehicle image through the Flask-based web interface.
- The image is received by the System and passed to the Preprocessing Module for resizing, normalization, and enhancement using OpenCV techniques.
- The preprocessed image is then forwarded to the CNN Model for damage classification.

2) Damage Classification:

- The CNN Model processes the input image and classifies the damage severity as *Minor*, *Moderate*, or *Severe*.
- The classification result is returned to the main system controller for further processing.
- The output is temporarily stored and sent to the Cost Estimation Module for analysis.

3) Cost Estimation and Recommendation:

- The Cost Estimation Module maps the classified damage level to a predefined cost range and generates an estimated repair cost.
- The system also provides an Insurance Recommendation, suggesting whether to file a claim or opt for self-repair based on the estimated cost.
- The final results, including damage level and cost details, are saved in the MySQL Database for record-keeping.

4) Result Display and Report Generation:

- The Web Interface retrieves the results from the database and displays them to the user in a clear, structured format.
- The user can view the results instantly and choose to download a PDF Report containing damage classification, cost estimation, and insurance recommendation details.

This sequence diagram ensures a clear understanding of how different system components interact step-by-step, depicting the real-time communication flow between the user, the AI model, and the database within the *DeepClaim* framework.

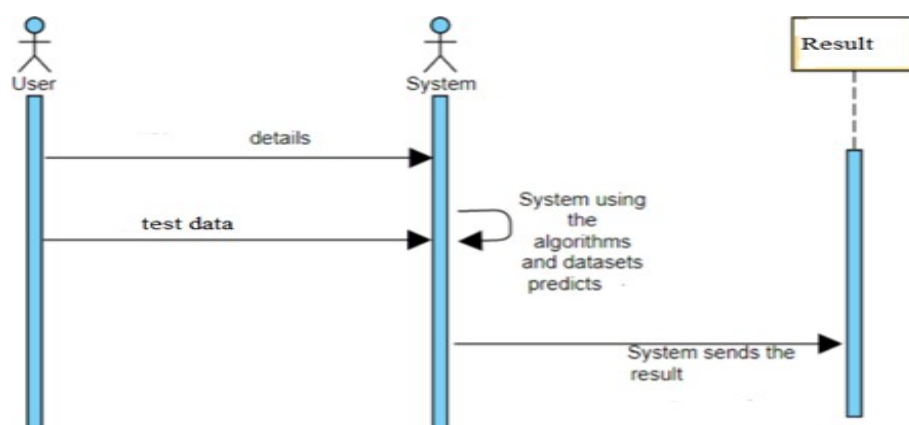


Fig.5 Sequence Diagram

XIV. SYSTEM IMPLEMENTATION

The *DeepClaim* system was implemented by integrating multiple AI-driven modules into a single, seamless framework for automated vehicle damage assessment and cost estimation. The development followed a modular architecture to ensure that each component could be independently developed, tested, and later combined into a unified application.

The implementation phase focused on performance optimization, scalability, and ensuring accurate communication between the frontend, AI model, and backend database.

A. Coding

The system was primarily developed using Python, leveraging various libraries for deep learning, image processing, and web integration. The core modules include:

- 1) Image Upload and Preprocessing Module – Handles image input from users, resizing, normalization, and enhancement using OpenCV for better model accuracy.
- 2) CNN Model Module – Built using TensorFlow and Keras, it performs damage severity classification into *Minor*, *Moderate*, and *Severe* categories.
- 3) Cost Estimation Module – Maps the classified severity level to a predefined cost range, generating an approximate repair cost.
- 4) Report Generation Module – Uses Flask and FPDF to display results and generate downloadable PDF reports containing severity, cost, and insurance recommendations.

The entire coding process emphasized modularity, code readability, and efficient integration of frontend and backend functionalities through Flask routing and API handling.

B. Integration of Modules

The integration process involved connecting all the modules into a continuous workflow to achieve end-to-end automation: Image Upload → Preprocessing → CNN Classification → Cost Estimation → Report Generation. The Flask-based web interface serves as the control center, allowing users to upload vehicle images and view instant results. Each module communicates smoothly via defined APIs, and data consistency is maintained through a MySQL database for storing image details, results, and reports. This integration ensures that the entire system works cohesively without data loss or process interruption.

C. Testing and Debugging

- To ensure system reliability and accuracy, multiple levels of testing were conducted:
- Unit Testing: Each module (preprocessing, classification, cost estimation, and report generation) was tested individually for functionality and stability.
- Integration Testing: Verified smooth interaction between the web interface, AI model, and database.
- Model Accuracy Testing: Conducted under various conditions of lighting, angles, and vehicle types to validate prediction accuracy.
- Performance Testing: Checked response time and load handling for multiple image uploads simultaneously.

Debugging focused on resolving issues related to Flask routing, model loading, image format compatibility, and database synchronization. After successful debugging, the *DeepClaim* system achieved stable performance with high accuracy and reliable cost estimations

XV.RESULTS AND OUTPUT IMAGES

The implementation of the *DeepClaim* system was successfully tested using real-world vehicle damage images to validate the accuracy and efficiency of all integrated modules. The results confirmed that the CNN model performed well in classifying damage severity, while the cost estimation module generated realistic repair cost predictions. The web interface functioned smoothly, allowing users to upload images, view results, and download reports without delay or error. The testing phase demonstrated that the system can accurately analyze damaged vehicle images under varying lighting and angle conditions, maintaining consistent performance:

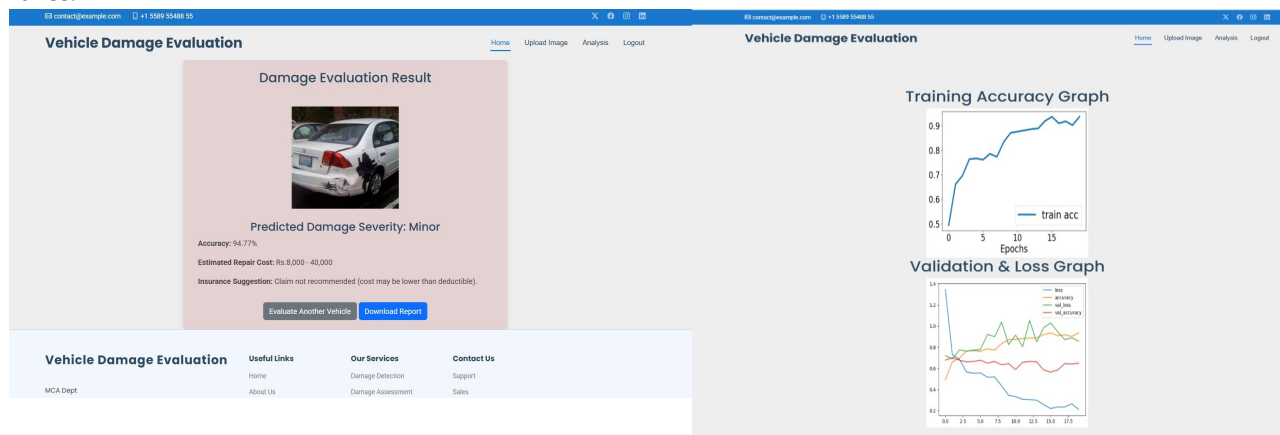


Fig.7 Final Output

The image illustrates the core functionality of the *DeepClaim* system. A damaged vehicle image is uploaded through the Flask-based web interface, where the AI model automatically detects the damaged area, classifies the severity as *Moderate*, and displays the predicted repair cost. The interface clearly presents the damage level, estimated cost, and an insurance recommendation (e.g., “Claim Recommended”) in real time. Once the analysis is completed, the system allows the user to download a detailed PDF report containing all the assessment results for insurance or repair use.

XVI. CONCLUSION

The *DeepClaim: An AI-Driven Framework for Automated Vehicle Damage Severity Assessment and Insurance Cost Estimation* present an innovative solution to overcome the limitations of traditional manual inspection and claim evaluation processes. Conventional methods of vehicle damage assessment often involve subjective judgment, time-consuming physical inspections, and inconsistent cost estimations. By integrating artificial intelligence, computer vision, and deep learning techniques, this project delivers a fully automated, objective, and efficient system for damage classification and cost prediction. The use of Convolutional Neural Networks (CNNs) ensures that the system achieves high accuracy across diverse vehicle images and environmental conditions, while the Flask-based web interface provides a user-friendly platform for interaction.

Experimental testing confirmed that *DeepClaim* performs effectively in real-world scenarios, accurately classifying vehicle damages into categories such as *Minor*, *Moderate*, and *Severe*, and generating corresponding cost estimates. The system’s modular design—comprising image preprocessing, damage classification, cost estimation, and report generation—ensures scalability and easy maintenance. Additionally, by providing automated insurance recommendations, the framework enhances transparency and assists both users and insurance professionals in making quick, data-driven decisions.

In conclusion, this project demonstrates the immense potential of AI-based automation in transforming the automobile and insurance sectors. The *DeepClaim* system is cost-efficient, reliable, and scalable, making it suitable for integration into real-time claim assessment workflows. It represents a significant step toward digital transformation in insurance technology and establishes a strong foundation for future developments, including mobile deployment, real-time damage localization, and cloud-based predictive analytics.

XVII. FUTURE ENHANCEMENTS

While the *DeepClaim* system has demonstrated effective performance in automating vehicle damage assessment and cost estimation, there are several areas where enhancements can further improve its accuracy, functionality, and scalability. One significant enhancement is the integration of cloud-based databases and storage, enabling users and insurance agents to access claim data and reports remotely in real time. This would ensure better data security, centralized record-keeping, and multi-user accessibility through both web and mobile platforms. Additionally, implementing advanced deep learning architectures such as YOLOv8, EfficientNet, or Vision Transformers (ViT) can enhance the precision of damage localization and classification, especially under challenging conditions like varying lighting, multiple damage zones, or complex vehicle surfaces.

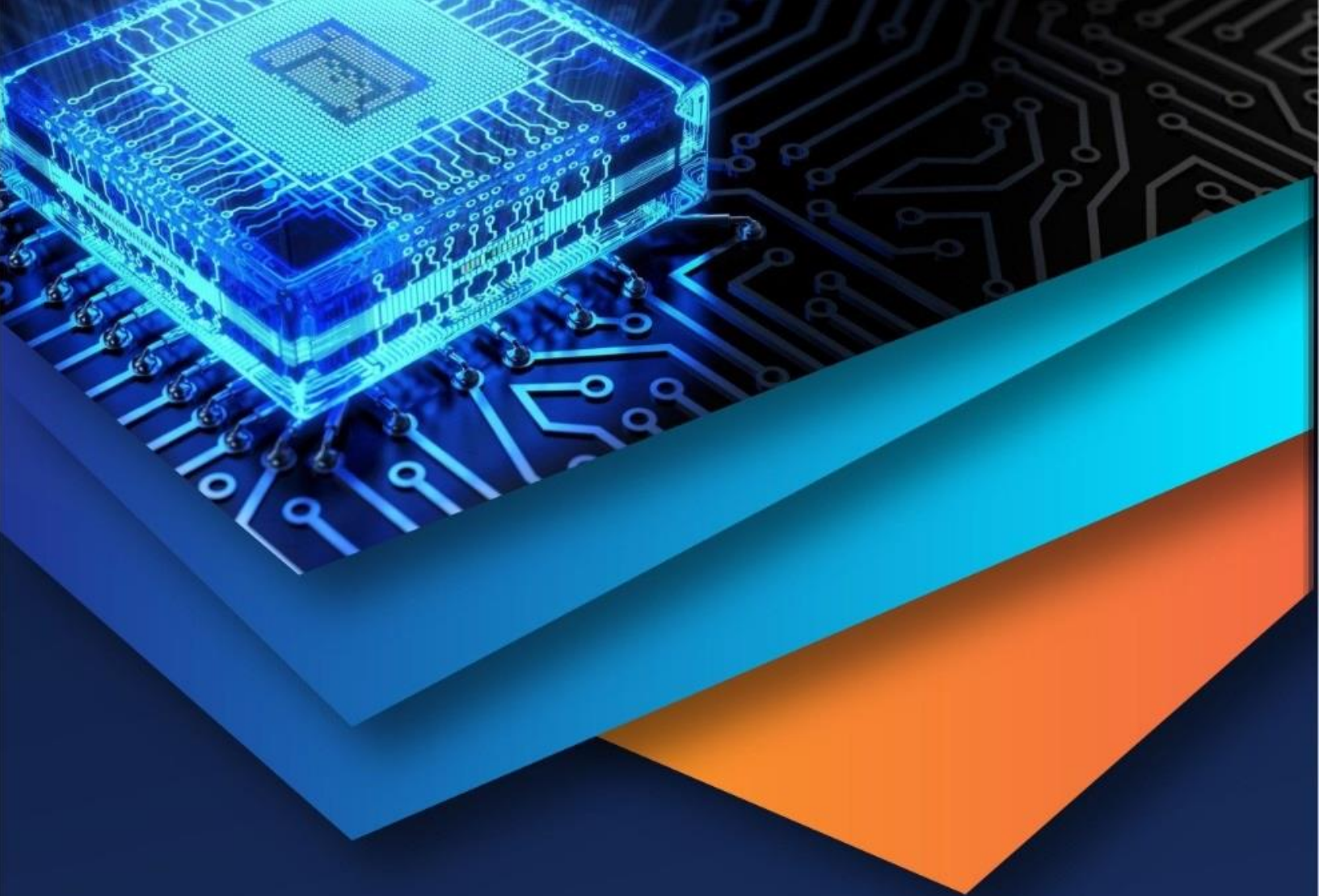
Another area of improvement involves multi-angle image support, allowing the system to analyze images captured from different viewpoints for a more comprehensive damage evaluation. Incorporating real-time object segmentation could help identify specific damaged vehicle parts and provide more detailed cost estimations. The system can also be extended to include automated claim verification by integrating APIs from insurance providers, enabling end-to-end digital claim submission and approval. Furthermore, the addition of a mobile application interface would make the framework more accessible to users on the go, allowing quick damage capture and instant analysis. Finally, using AI-based predictive analytics for trend analysis and fraud detection could further enhance the reliability, transparency, and trustworthiness of automated vehicle insurance systems.

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