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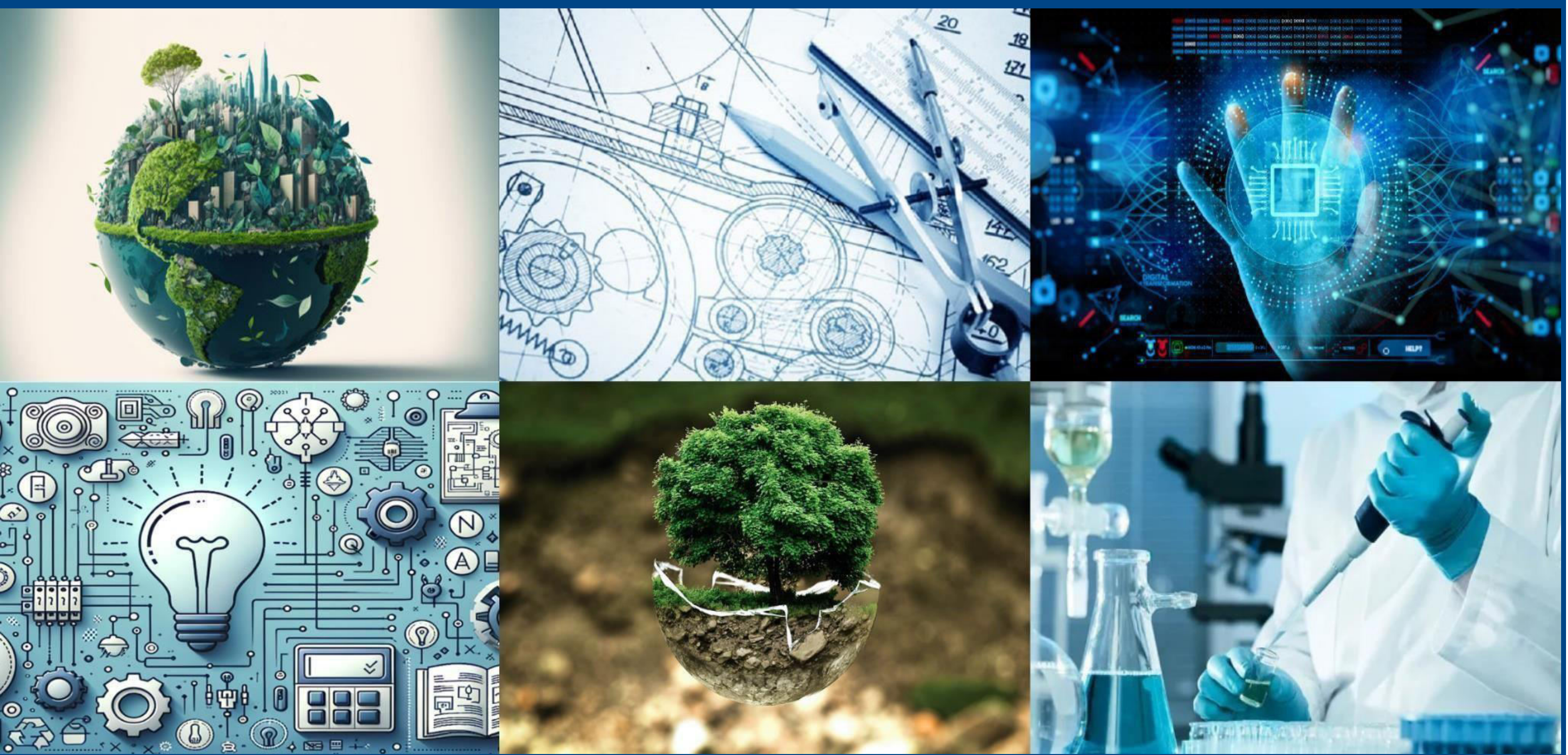

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# "VehiCentra: WHERE DAMAGE DETECTION MEETS INSTANT TOOL"

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**ABSTRACT:** Accidents are stressful, and claiming vehicle insurance often adds to the frustration with long inspections, paperwork, and delays. Vehicentra, where damage detection meets instant claims, aims to make this process faster, smarter, and more transparent. Using image recognition and artificial intelligence, Vehicentra can detect vehicle damage from a photo, assess its severity, and estimate repair costs in seconds. The system also predicts the likely insurance payout based on policy details, deductibles, and coverage limits. This gives users clarity before they file a claim. The process is simple. Users upload an image of the damaged vehicle through a mobile or web interface. AI algorithms identify and classify the damage, calculate repair costs using market data, and generate an insurance estimate. With a single click, users can submit the claim instantly. This eliminates multiple visits and lengthy waiting times. For vehicle owners, Vehicentra ensures fast service and clear claims without hassle. For insurers, it reduces operational costs, improves accuracy, and helps detect a fraudulent claim. By combining AI-driven damage assessment with instant claim initiation, Vehicentra turns a slow, manual process into one that is quick, reliable, and user-friendly. It sets a new standard for the future of insurance services.

**KEYWORDS:** Convolutional Neural Network, Artificial Intelligence, Deep Learning

## I. INTRODUCTION

Owning a vehicle offers freedom and convenience, but it also comes with the risk of accidents and unexpected damage. While insurance is meant to ease the financial burden after such incidents, the reality is often stressful. Traditional claim processes involve lengthy inspections, piles of paperwork, and days or even weeks of waiting for approvals. This not only frustrates vehicle owners but also creates inefficiencies for insurance companies. This project is designed to change that experience entirely. By combining artificial intelligence, computer vision, and predictive analytics, the system can assess vehicle damage from just a photograph. It then provides an accurate repair cost estimate and predicts the insurance payout amount, all within minutes. The process is user-friendly. A photo of the damaged vehicle is uploaded via a mobile or web application, and the AI engine detects, classifies, and measures the extent of the damage. It integrates real-time market data to calculate repair costs and applies policy-specific rules to predict claim amounts. Users can even start their claim instantly through the platform. By removing delays and increasing transparency, Vehicentra benefits everyone. Customers gain clarity and speed. Insurers reduce costs and fraud. Repair shops receive faster approvals. This project represents a step toward a smarter, faster, and more reliable future for vehicle insurance claims

## II. LITERATURE SURVEY

[1] X. Wen, L. Shao, W. Fang, and Y. Xue tackle the problem of selecting Haar-like features for vehicle detection and classification. Haar-like features suit this task because they provide a compact representation, capture edge and structural details, work across different scales, and can be calculated efficiently. Given the large number of possible features, the authors suggest a quick and effective selection method using AdaBoost. This method combines each sample's feature value with its class label. Theoretical insights and experimental results confirm the efficiency of their approach. They also introduce an improved normalization algorithm for the selected features to reduce variation within classes and enhance distinction between classes.

[2] P.A. Viola and M.J. Jones propose a machine learning-based method for visual object detection that processes images quickly while maintaining high accuracy. Their work is significant for three main reasons. First, they present the "integral image" representation, which allows for rapid calculation of the detector's features. Second, they create an

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AdaBoost-based learning algorithm that selects a small but highly effective subset of visual features from a large set, leading to efficient classifiers. Third, they design a cascade architecture that combines more complex classifiers, enabling the system to swiftly discard background areas and focus more computational resources on promising object-like regions. This cascade acts as an object-specific mechanism for directing attention, providing statistical assurance that discarded areas are unlikely to contain the target object.

[3] B. Prachi, D. Kasturi, and C. Priyanka point out that road accidents and traffic congestion are major problems in cities. Without effective accident detection technology, delays in ambulance arrival, often made worse by traffic, significantly lower a victim's chances of survival. To tackle these issues, they propose a smart accident detection and response system. This system uses in-vehicle sensors for automatic accident detection and includes a GPS and GSM module to send the accident location to a central server that keeps a database of city hospitals. The nearest hospital is then notified, and an ambulance is sent to the scene. Additionally, radio frequency-based traffic light control along the ambulance's route minimizes travel time to the hospital, improving emergency response efficiency and reducing fatalities.

**EXISTING SYSTEM**

The current process for assessing vehicle damage and handling insurance claims is mostly manual. After an accident, the vehicle owner contacts the insurer. A surveyor then inspects the damage, takes photographs, and prepares a cost estimation report. This traditional method is time-consuming and can take several days for approval. It is also subjective, as different assessors may provide different estimates for the same damage. Some insurers have started using mobile apps to submit photos, but the evaluation still relies heavily on human judgment. This leads to delays, higher operational costs, and inconsistent claim settlements, which affects customer satisfaction.

**PROPOSED SYSTEM**

We collected a dataset of both normal and crashed vehicles. We then preprocessed the vehicle images using resizing methods. Create Dataset: The dataset includes images of crashed cars and normal cars that have not been in any accidents. We split this dataset into training and testing sets. Image Pre-processing: We adjusted the dimensions and formatting for model training. Training: We used the pre-processed training dataset to train our model with a CNN-based transfer learning algorithm. Classification: Our model classifies images to show whether a car is crashed or not. It also estimates the cost for insurance claims. SMS Alert: If the car is detected as being 15 years old, an SMS alert will be sent to the user with this information.

## III. SYSTEM ARCHITECTURE

The data flow diagram shows how user-captured vehicle images move through ingestion, preprocessing, damage detection, cost estimation, and claims processing. This flow results in auto-settlement or human review, with all data securely stored and logged. The diagram illustrates the sequence from input (images) to output (settled or escalated claim), highlighting transformation, decision points, and secure storage. A data flow diagram visually maps the flow, transformations, and storage of data, helping clarify complex processes.

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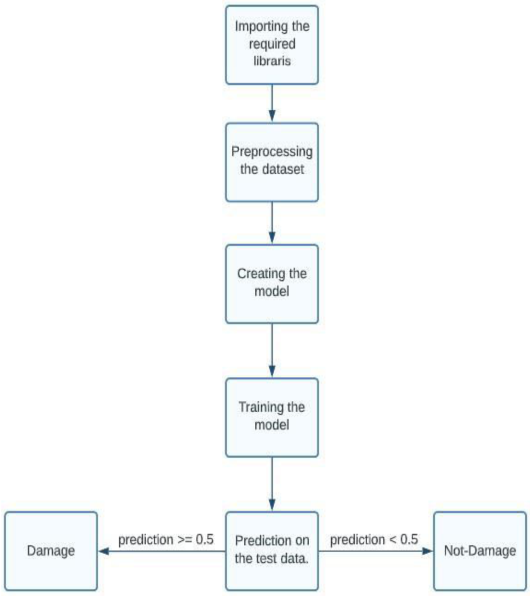


Fig .1 System Architecture

## IV. METHODOLOGY

Convolutional Neural Networks (CNNs) are a type of multilayer perceptron that has regularization built in. In a standard multilayer perceptron, every neuron in one layer connects to all neurons in the next layer. This can often lead to overfitting. Common ways to prevent overfitting include penalizing parameters during training, such as using weight decay, or reducing connections, like dropout and skipped connections. CNNs, on the other hand, use a different method. They take advantage of the structure of data and build complex patterns from simpler, smaller patterns found in their filters. This approach results in less connectivity and complexity than fully connected networks. The design of CNNs draws inspiration from how biological vision systems work, particularly the visual cortex in animals, where neurons react only to certain areas of the visual field, known as receptive fields. These receptive fields partly overlap, allowing for complete coverage of the visual space while keeping localized sensitivity.

## V. DESIGN & IMPLEMENTATION

Your system is set up as a modular, service-oriented process that changes user-submitted car images into actionable insurance claims. It begins with a frontend, either a mobile or web app, that collects images and metadata, including policy ID, VIN, and GPS. This is followed by an ingestion service that checks the inputs and sends them to preprocessing. Here, images are standardized and anonymized. For example, license plates are blurred using object detection and Gaussian blur techniques, as is common in privacy-focused computer vision systems. After preprocessing, an ML inference pipeline takes over. Architectures like Mask R-CNN allow for precise location and segmentation of damage areas. The advanced SLICK architecture improves accuracy by combining structural priors, attention blocks, and part-aware segmentation—especially useful for complex or hidden damage. Once damage is detected, classification and severity estimation models identify the type (scratch, dent, crack) and assess the severity of the damage. Next, the cost estimation engine translates severity scores into dollar amounts using rule-based logic, which adds labor hours to part prices. Future upgrades may include using ML regression on previous claims data. The claims orchestrator enforces policy rules, detects fraud, and either automatically settles eligible claims or passes others to human adjusters. All images, estimates, and decision metadata are securely stored with encryption and audit logs to ensure compliance and resolve disputes.

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## VI. OUTCOME OF RESEARCH

Vehicentra can transform insurance claims by automating how we assess damages. Case studies show that AI systems can reduce claim resolution time from days to minutes. This improves both efficiency and accuracy. Automated workflows lower manual errors, cut operational costs, and shorten settlement cycles. This creates smoother claim experiences for insurers and policyholders. These benefits fit with a larger trend: AI adoption in insurance grew from 48% to 71% in 2025, leading to real financial results like cost savings and increased revenue. On an industry level, the global market for AI-powered insurance claims automation is growing quickly. It is expected to rise from about $0.39 billion in 2024 to $0.85 billion by 2029, with a 16.6% compound annual growth rate (CAGR). Tractable, a leading AI company in this area, has reached unicorn status by providing fast, image-based damage assessments in various countries. However, real-world challenges remind us to be careful. Some AI scanners have incorrectly identified existing damage, leading to billing disputes, even when human reviews caught these earlier. This highlights the need for transparency, reliable metadata, and human oversight in Vehicentra design. Overall, Vehicentra has the potential to significantly reduce time-to-settle, lower costs, and improve customer satisfaction, as long as it is built with precise validation and strong safeguards.

## VII. RESULT AND DISCUSSION

The Vehicentra system aims to automate vehicle damage assessment and simplify insurance claims by using image-based AI and guided workflows. In practice, insurers that use similar photo-first strategies see faster turnaround times. Agents can settle hundreds of low-cost claims in minutes, increasing operational efficiency and improving customer experience. For example, PwC created a three-model pipeline for damage detection, part mapping, and reference-image retrieval. This pipeline provided estimates that human adjusters found accurate and trustworthy, particularly when supported by explainable AI visuals. However, estimates driven by AI also face some issues. Body shops have expressed concerns about the inaccuracy of photo-based assessments. They report discrepancies that delay repairs and weaken trust. There has also been an increase in sophisticated fraud, including AI-generated or "shallowfake" images. In the UK, the incidence of fake-damage photo claims rose nearly 300% between 2021 and 2023, significantly affecting rising premiums. Rental companies using AI scanners have also faced criticism for wrongly charging for damages, often due to timestamp errors, although many disputes were resolved after human reviews.

**DISCUSSION SUMMARY**

Vehicentra could revolutionize claim settlement by delivering rapid, cost-effective, and customer-friendly processing. To sustain this upside, it must integrate robust explainability, strict fraud defenses (e.g., metadata validation, anomaly detection), and transparent human-in-the-loop governance to maintain accuracy, fairness, and trust across the workflow.

## VIII. CONCLUSION

In this project, we successfully implemented a deep learning-based system for car crash detection using transfer learning with the MobileNet architecture. The model was trained on a dataset containing both damaged and undamaged vehicle images. After training, the model effectively classified the test images and, upon detecting a crash, sent an SMS alert to the user to encourage immediate safety measures. To address the issue of identifying vehicle damage for insurance and repair purposes, the proposed approach leverages a CNN-based detection technique optimized through transfer learning. Despite being trained on a relatively small dataset, the model achieved promising results and demonstrated the ability to generalize well to various types of car damage. Future enhancements could include expanding the dataset with more diverse images captured under different lighting and weather conditions, enriching image quality through edge enhancement, and improving the accuracy of damaged area localization through refined segmentation techniques. Additionally, the model can be extended to estimate repair costs by analyzing segmented damage regions and extracting relevant part-level information.

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