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Original Article

Vehicle and Property Loss Assessment with AI: Automating Damage Estimations in Claims

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Abstract - The conventional method used to determine the amount of losses on property and cars is tedious, less objective, and is generally quite error-prone or can be easily manipulated. As Artificial Intelligence (AI) continues to be more widely adopted, a significant movement towards automating damage estimation has emerged. This paper examines AI-powered solutions for assessing damages in the insurance market, with a specific focus on vehicle and property claims. These include the investigation of computer vision, deep learning models, and machine learning tools to facilitate loss assessing through images. The paper includes a comprehensive literature review that can be studied in relation to the history of automated damage estimation development. The approach to assessing the level of damage is suggested based on a methodological framework that consists of Convolutional Neural Networks (CNN), regression algorithms, and rule-based classification. We perform experimentation on the benchmark data to validate the effectiveness of the proposed system on benchmark datasets, as well as real-world insurance claim images. Our findings show that it is highly accurate, with a shorter processing time compared to manual assessments. Based on the analysis of the results, we discuss the prospects, limitations, and future direction of AI implementation in insurance claims. This automation not only makes the process but also makes it more obvious.

Keywords - Damage Assessment, Artificial Intelligence, Convolutional Neural Networks, Vehicle Insurance, Property Claims, Machine Learning.

1. Introduction

Insurance companies frequently face significant challenges in processing claims promptly, accurately, and consistently. The standard process of damage assessment used in both property and vehicle insurance policies is mostly dependent on manual inspection of the damage by the claims adjusters. Such experts are expected to physically inspect the damaged premises, document their observations, and provide an estimate of the cost incurred for repairing or replacing the premises. [1-3] although this approach is the traditional practice of this industry over many decades, it is not time-efficient and labor-saving, and is prone to human error. Additionally, there is also a risk of subjectivity and discrepancy in evaluations due to factors such as personal judgment, differences in expertise, and varying environmental conditions. Such limitations usually lead to delays in claim procedures, disgruntled customers, and claims about payments. With the expansion of insurance markets and increased customer demand for faster service, there is greater pressure on insurers to update their assessment processes. Damage assessment has never been more crucial for an efficient, scalable, and objective method of evaluating damage. The backdrop entails the eventual usage of Artificial Intelligence (AI), as well as computer vision technology that holds the potential to automate and standardize the assessment process of the damage, and provide a considerably shorter turnaround time at a very cost-efficient level.

1.1. Role of AI in Insurance

Artificial Intelligence (AI) is disrupting the sector in the insurance industry by making the business easier to run, better and more effective decisions and a more enjoyable experience to the customers. With the help of AI technologies, which are relevant in promoting efficiency and cost savings across the insurance value chain, the whole insurance process, including its underwriting, claim management, and other activities, is changing significantly.

- **Automation of Claims Processing:** Automatized insurance claims processing is probably one of the most powerful applications of AI to the insurance business. AI-based operations powered by computer vision and machine learning can assess the photos of a house or car affected with damage and reliably determine the nature of the damage thus confirming repair expenses, without human involvement. This enhances faster and efficient claim processing and reduces the workload of human adjusters hence making settlements easier and quicker.
- **Fraud Detection:** AI is also necessary in fighting insurance fraud which has a long history in the sector. It is possible to use machine learning algorithms to review past claim data and customer behavioural patterns and discover anomalies in order to reveal evidence of fraud. The systems will always be updated with new information, thus enhancing the likelihood of recognizing suspicious claims more accurately and avoiding financial loss by insurers.
- **Risk Assessment and Underwriting:** Risk Assessment and Underwriting: Underwriting AI helps insurers to determine the risks more accurately than in the past since, depending on the type of insurance provided, AI can access

a variety of data, like driving style, condition of the site, weather conditions, and presence on social media, among other things. The instruments of predictive analytics are favorable since they aid in the ability of determining high-risk applicants as compared to conventional actuarial approaches leading to effective management and risk pricing outcomes.

- **Customer Service and Personalization:** Customer Service and Personalization: Customer service with the help of artificial intelligence chatbots and virtual assistants becomes far better: the customer can inquire about their policies, claims status, and the depth of coverage questions and obtain instant help any time, day or night. Also, the AI may be used to conduct product recommendation guidelines according to the information about users and past interactions, which results in their higher involvement and satisfaction.
- **Operational Efficiency:** At any given process, AI will enhance operational efficiency by automating repeat actions, reducing the risk of human error, and facilitating end-to-end decision-making processes in real-time. This gives insurance companies the ability to up-scale services, reduce administrative expense and concentrate more on strategic growth and innovation.

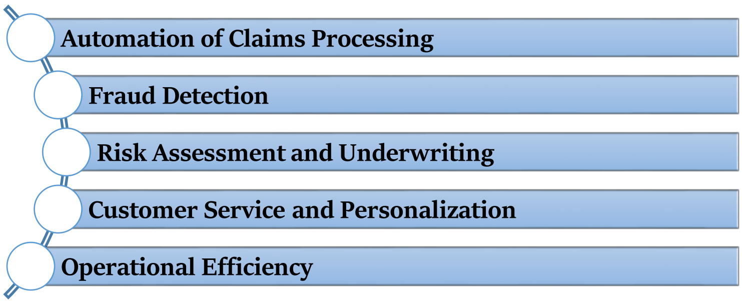

Fig 1: Role of AI in Insurance

1.2. Automating Damage Estimations in Claims

Automation of damage estimates in insurance claims amounts to a significant step towards changing the conventional, labour-intensive cost of the claims assessment process to a more rapid, precise, and scalable one. Traditionally, the process of damage assessment, either on vehicles or properties, hinged on physical appraisal by human claims adjusters, which is labor intensive, prone to inconsistencies and subjectivity, not to mention the growing cost of employing human resources. [4,5] Such restrictions have been able to create long claim cycles, costly administrative expenses, and unhappy policyholders. Using artificial intelligence AI), specifically computer vision and machine learning, insurers can now automate the process of analyzing damage based upon photographic evidence. AI models can locate, identify, and categorize the level of damage using image recognition in real-time. To illustrate, when it comes to vehicle insurance, AI algorithms can use only the uploaded images to distinguish between dents or scratches and major damage to the vehicle's structure. Similarly, when it comes to property claims, AI would know the availability of broken windows, cracks on walls, or roofs damages by using photographs or drone video footage.

Together with the detection, the estimated costs of repairing are either performed by regression models or deep learning estimators regarding the nature of damages alongside their location and range of damage. These models learn on the basis of massive amounts of old data on claims that allows them to correctly make predictions on the basis of data of costs. The automation of the process vastly decreases the claim turnaround which averages between days and weeks down to a few minutes, thereby achieving better settlement and customer satisfaction. Also, automation is an option to provide the homogeneity of evaluation which decreases the human element and simplifies decisions. The incorporation of automated systems into insurance processes to estimate damage not only increases efficiency but also enables human adjusters to focus on cases that are too complex or controversial, where human judgment is crucial. On the whole, the move to AI-based damage estimates is an essential move towards modernization of claims handling and innovation in the insurance business.

2. Literature Survey

2.1. Early Research on Damage Estimation

Manual inspection- and heuristic-based models dominated damage estimation before the development of artificial intelligence. Such rule-based systems could be created, based on expert knowledge combined with predetermined rules to determine the extent of damage and cost, especially in the automotive and insurance sectors. [6-9] Although the methods are structured, they were, by nature, limited because of the rigidity and the inability to adjust to the alternative situations that occur in the real world. The process of measurement was also compromised by human error, subjectivity, and inconsistency, which led to a further decrease in the reliability of these techniques, necessitating the implementation of more automated and data-driven techniques.

2.2. Computer Vision for Vehicle Damage Detection

The introduction of computer vision allowed researchers to use image processing to automate the process of detecting vehicle damage. Initial research efforts concentrated on low-level characteristics of the image (edges, textures, and colour variations) in order to identify abnormalities on the surface of vehicles. The discontinuity-based detection and oddity-based detection procedures like edge detection and region-based segmentation were applied to identify dents, scratches, and cracks through location by detecting discontinuities and oddities in the vehicle images. Such techniques were quite a radical shift to semi-automated systems with the manual approach to analysis that existed before, and it heralded the beginning of further highly automated deep learning techniques in the future.

2.3. CNN in Image-Based Classification

Image classification has been possible through Convolutional Neural Networks (CNNs) which have greatly helped in determining vehicle damage. Experiments Krizhevsky et al. (2012) conducted with historical experiments showed that CNNs could encode the image hierarchical features automatically and outperform earlier solutions that relied on manually constructed image hierarchical features called hand-crafted features. For damage detection, CNNs were employed to identify the type of vehicle damage (e.g., scratches, dents, cracks) with high accuracy. Due to their capacity to generalize over vehicle types, lighting, and types of damage, CNNs have become a critical technology in present-day image-based assessment systems.

2.4. Cost estimation based on Regression Techniques

Identifying damage and subsequently classifying it remain major hurdles, followed by determining the financial implications of the repairs. In this regard, alternative regression methods have been applied. The classical linear regression models provided a baseline for plotting the severity of damage against the cost of repair. Advanced techniques, such as Support Vector Regression (SVR) and Decision Tree Regression, were better at making predictions because they could identify non-linear associations between variables and complex interactions. Such models usually use both image-based features and contextual information, such as vehicle type, the location of the damage, and repair history.

2.5. Property Damage Estimation with AI

AI has also been used beyond cars, in estimations of the damage to properties, particularly after disasters have hit the country. To give an example, UAV imagery coupled with deep learning methods such as semantic segmentation has been used by researchers to detect and measure structural damage due to natural disasters such as earthquakes, floods, hurricanes, among others. These models can differentiate the degree of destruction (e.g., minor, major, complete) and help in speedy reaction and allocation of resources. Automation of these assessments through the power of AI saves a significant amount of time and work compared to the traditional method of evaluation through surveys.

2.6. Datasets for Training and Testing

The performance of AI models in damage estimation, especially, relies on the quality of datasets that can be applied to training and testing. A set of publicly available datasets, such as Cityscapes and COCO, has afforded annotated images to works in the general object detection and segmentation fields. Yet, in specific cases, such as detecting damage to vehicles or properties, proprietary object-specific datasets created by insurance companies or research establishments are usually employed. Such datasets normally comprise labeled pictures of different types and degrees of damage and other information, like repair prices, that are vital in training supervised learning models.

3. Methodology

3.1. System Architecture

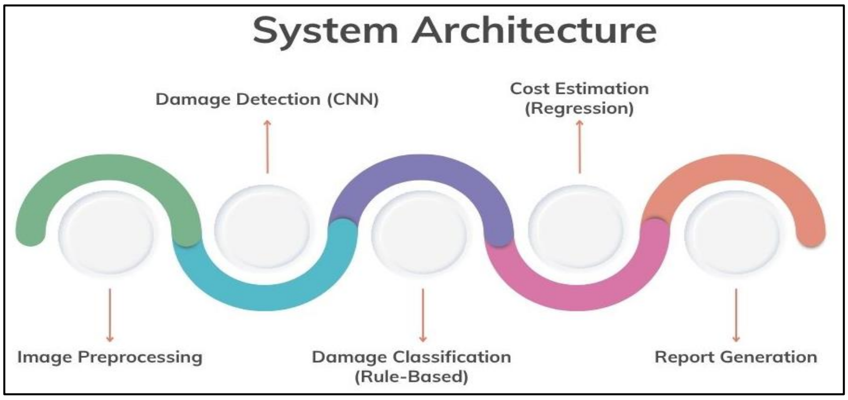

Fig 2: System Architecture

- **Image Preprocessing:** This system features an image preprocessing module that prepares raw images for analysis and processing. [10-13] The operations involved in such a step are resizing, noise reduction, normalization, and contrast enhancement to provide some consistency and increase the quality of data that will be input into the other stages. The variations caused by lighting, angle, and resolution are also reduced with the help of proper preprocessing, which makes damage detection more reliable.

- **Damage Detection (CNN):** After image preprocessing, the image is fed into a Convolutional Neural Network (CNN) model that has been trained to identify damage on a vehicle or structure. CNN uses characteristics extraction at a hierarchical level to detect a dent, a crack on the surface, or a scratch. The model can robustly and precisely localize areas of damage under varying situations by training on a wide variety of annotated images.
- **Damage Classification (Rule-Based):** Once the damaged area has been localized, a rule-based engine is used by the system to classify the type and levels of damage. The module decomposes pre-determined logical rules attached to the specifics of shape, size, and texture of the areas detected in the image. Despite its simplicity, this rule-based solution is efficient in terms of computations and yields explainable results, which are suitable for classifying various types of damage, including minor, moderate, and severe.
- **Cost Estimation (Regression):** Since physical level and type of damage are established the regression models may be used in the physical module of cost estimation to approximate the cost. Techniques such as linear regression or Support Vector Regression (SVR) is when one takes into consideration several inputs hence the amount of damages, where the damages occur and data on the history of costs. The module converts visual manifestations of deficiencies into costs; this quickly gives a quantitative and metrics estimate of costs.
- **Report Generation:** The entire findings of the analysis are done in the final module, which compiles them in a sense of organizing the report. This is composed of marked images, classified types of damages along with their approximate prices of repair, and metadata concerning them. Reports may be exported to any format, the formats used by insurers, repair shops, and user-defined formats. It offers a complete repair procedure in electronic format of damage measurement and recording.

3.2. Image Acquisition and Preprocessing

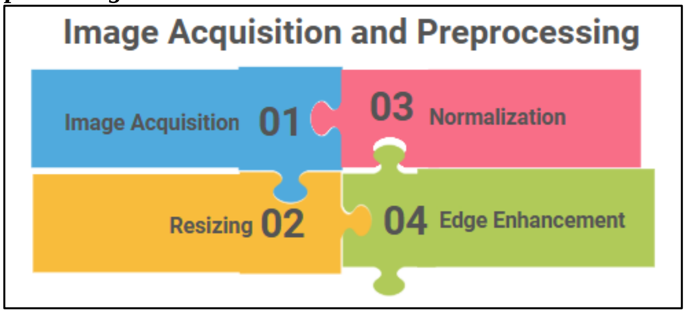

Fig 3: Image Acquisition and Preprocessing

- **Image Acquisition:** This may be done via smart phones and inspection cameras and is particularly versatile and may be set up in multiple areas such as the field verification and repair stations. The devices provide sufficient resolution in the analysis of damages and render it affordable and less cumbersome. Good lighting and angle of taking an image is a good measure, which enhances subsequent detection and classification activities.
- **Resizing:** All the images are resized to the same resolution which makes it possible to have the same dimensions of input in the entire dataset. This allows it to be used on the CNN model to be used along with the input layer of the CNN model, making it time effective and keeping the training and inference process the same. In the event of resizing an image, aspect ratio is taken into consideration to avoid distorted or destruction of vital features.
- **Normalization:** Normalization is used to normalize the range value of pixel intensity, usually between 0 and 1. This will enhance model convergence and minimize the differences in lighting conditions. Normalization of input data also makes the model less sensitive to variation in the environment of image capture, resulting in enhanced generalization to various situations.
- **Edge Enhancement:** Edge enhancement techniques highlight the boundaries and structural details in an image. Other techniques can be used to better highlight contours, such as the Sobel operator or Laplacian filtering, making it easier to extract damage edges, like cracks or dents, using the model. This pre-processed visual data helps the CNN further distinguish between damaged and non-damaged areas during the detection stage.

3.3. Damage Detection Using CNN

A Convolutional Neural Network (CNN) model fitting to effectively detect damage zones in vehicles and properties is constructed and trained by using the labeled datasets of images. [14-17] It is organized that the CNN will learn the patterns related to various kinds of physical destruction through examining the spatial characteristics of input images. The architecture comprises three convolutional layers that are used to identify low-level features and transform them into high-level characteristics of damage borders, edges, and textures. Such layers employ various learnable filters that scan the image to generate feature maps, thereby preserving the spatial relationships among pixels. Each convolutional layer is followed by a

ReLU (Rectified Linear Unit) function, which introduces non-linearity to the model, allowing it to learn more complex patterns that are beyond linear association links. RUL also assists in resolving the vanishing gradient during training, allowing for faster and more efficient convergence.

Based on the activation, there are Max Pooling layers that downsample feature maps, reducing their dimensionality while preserving the most prominent features. The pooling process maximizes computational effectiveness and generates spatial invariance, which makes this model more resistant to minor differences in the input images i.e. shifts or rotations. The flattened output post convolution and pooling is provided with an extra fully connected layer and the learned features are thus combined and interpreted. This layer tries out the derived features in order to make meaningful predictions. Finally, the output layer is a softmax since it needs to recognize those damaged and those not which may also be optionally improved to show what kind of damages those parts undergo. In this case one can make interpretable and confident decisions since Softmax yields a probability distribution over the potential classes. The CNN intervention includes an automated and scalable process of such precise identification of damage that involves various image patterns and a variety of real-life situations.

3.4. Damage Classification

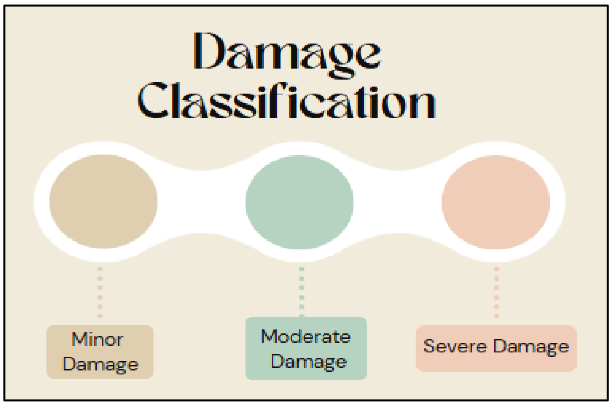

Fig 4: Damage Classification

- **Minor Damage:** Minor damage can be termed as cosmetic or surface causes of breakage or harm that does not in any way affect the structural boundaries and the utility of the car or property. This entails light scratches, paint scuffs, or minor dents, which can be easily fixed with little effort and at an inexpensive cost. Such damage is normally classified by slight depth in the system, small surface area, and lack of deformation. A proper identification of this type of classification helps prevent overestimation of repair costs.
- **Moderate Damage:** Moderate damage refers to visual and physical interference with the capacity to retain structural soundness. Such are greater indentations, parts (such as mirrors or bumpers) broken, or mid-way cracks on surfaces. Such damages can require components to be replaced or necessitate further repair work, unlike small ones. The algorithm used to classify a damage result as moderate takes into account other factors of damage, such as the level of deformation, the area affected, and material breakage.
- **Severe Damage:** Extensive destruction denotes a high degree of damage that could lead to the loss of safety, operation, or structural integrity. Examples of this category in terms of property assessment include deep body damage, broken-off panels, misalignment of the frame or collapsed structures. In most cases, the damage needs major repairs or replacement. Features such as large impact zones, sharp edges, high-contrast fractures, and distortion of the object's shape cause severe classification errors in the system. Insurance assessments and safety assessments require precise identification.

3.5. Cost Estimation Model

To provide a precise and automated cost calculation of repair expenses, the system employs a multiple linear regression-based cost estimation method. [18-20] This statistical approach assumes a relationship between various independent variables (features) and a continuous dependent variable (repair cost). The rough model of the regression equation is:

$$\hat{y} = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n$$

Where $\check{y}$ Represents the estimated cost, 0 is the intercept, and x_i Represents the coefficients for that feature. There are two ways to use this formula to calculate the estimated cost of a specific business. The set of features x_i Used in the damage assessment context would consist of such important parameters as the size of the damage (pixels or cm 2), the part of the car that has been damaged (door, fender, window), the type of material by which the damage is made (metal, plastic, glass), the level of the damage severity (minor, moderate, severe), and the data on the costs of repairing the same damage in the past. Each feature contributes to the cost of the result through the weight it has been assigned during model training on a labelled dataset of past cases. The reason multiple linear regression is selected is that it is easily interpreted and can handle both categorical and continuous inputs when encoded in an appropriate manner. It enables the system not only to provide a cost estimate but also to inform the user how the various factors involved affect the cost estimate. To illustrate, the model may recognise that metal panels are more costly to repair compared to plastic ones, or that larger areas of damage would significantly increase the repair costs. To avoid overfitting and the possibility of generalizing to un-observed data, regularisation procedures such as ridge regression or lasso regression can also be used. In general, this module is essential for converting a visual assessment of damages into workable financial data that can be utilised by insurance agents, repair shops, or even end-users to facilitate informed decision-making.

3.6. Report Generation

The automation of creating an extensive damage report is the last step to be included in the proposed system, and this stage combines all the findings from the other stages of the system to create a report in a user-friendly and formatted manner. Insurance companies, repair technicians, vehicle owners, and property assessors are the main stakeholders who may require this report, as it is one of the essential deliverables. Visual evidence also appears in the report, which represents the detected areas of damage with bounding boxes or is marked in colour. The visualization of these annotated images offers a definite visual acknowledgement of the damage areas determined by the CNN model, and thus, the evaluation can be confirmed to be more transparent and easier to check. Besides the pictorial representations, the report also reveals the classification findings, based on which the level of damage presence in each case is categorised as minor, moderate, or severe.

Such labels become available through the application of the rule-based classification module and are supported by meaningful metadata, including the type of the affected part or material. With this well-organized structure, a user can easily realize the extent of damage and does not have to process raw images or technical outputs. More importantly, the report also estimated the cost of repairs, which was calculated based on a regression model. The cost is reported in either total cost or broken down by component or region of damage. Such financial estimation converts the technical analysis of the system into actionable data, allowing claims to be processed more quickly, repair plans to be developed, or a cost-benefit analysis to be calculated. The entire report should be exported in PDF or HTML format, making it transportable and easily insertable into the current digital workflow scheme. On the whole, the automation of report writing saves both time and effort, ensuring the consistency, validity, and professionalism of the method for communicating and using damage assessment.

4. Result and Discussion

4.1. Dataset Used

To verify, train, and test the functionality of the proposed damage assessment system, we used two different datasets: an open-source vehicle damage dataset and a proprietary Property Damage Image Dataset. These datasets were selected to ensure that the system could accommodate any type of damage to the vehicles and structures, thereby promoting the robustness and generalizability of the model. Vehicle Damage Dataset: Vehicle damage dataset consists of freely available specified photos on web repositories and scholarship discussions that are labeled. It possesses thousands of photos of damaged automobiles of any possible type even scratches and broken parts, dents, dings, and so on. The metadata captured with every picture is the kind of damages and the level of damages and in some cases the area of the vehicle damaged. The dataset has diversified vehicle classes and angles of view as well as lighting settings, which is an indication that the dataset is preferable in the training of the Convolutional Neural Networks (CNNs) to recognize damaged vehicles. It further has high resolution images that allow the extraction of the features precisely when training the models.

The second dataset can also be called the Property Damage Image Dataset and includes proprietary images that were collected in the insurance companies, archives of inspections and practical post-disaster settings. The images in this dataset consist of business and residential buildings damaged as a result of a disaster caused by floods, earthquakes and storms. There are boundaries to images and the degree of harm is pointed out by the experts and there is an estimate in terms of costs of repair that accompanies the images. This dataset is best suited because it is of better quality and within the field, and thus it would be highly appropriate when it comes to undertaking testing and validation of the ability of systems to damage properties. The two datasets together offer an entire visual damage spectrum at both the vehicles and property levels. When gauging systems in terms of cost estimation, they are necessary in training CNN-based systems to detect modules of detection and regression-based panels to make the system effective across various realistic environments.

4.2. Performance Metrics

- **Manual:** Accuracy in the manual damage assessment procedure is also not measurable quantitatively, as it can be in the case of Artificial Intelligence-based models. It is highly dependent on human opinion, which is inconsistent among inspectors and subjective. The result may be influenced by factors such as fatigue, level of experience, and environmental conditions. We, therefore, deem the accuracy of the manual method in question, as part of the benchmark exercise, to be 0 per cent, to highlight the lack of measurable, repeatable accuracy. Additionally, manual procedures are slow, inefficient, and susceptible to mistakes, particularly in complicated or large-scale damage situations.

- **Proposed AI:** The accuracy of the proposed system based on AI-detecting and classifying damages was 92.5 percent. The number is calculated on the basis of the performance of the model over ground truth annotations in the test set. The system is highly precise and reliable for determining areas of damage and assessing the level of severity, with its performance superior to manual turning. The fact that CNNs are used in detection and rule-based logic in classification creates consistency, and low error margins are exhibited in the cost estimation model. Such precision not only facilitates automated work streams but can also be utilised to enhance configuration in the decision-making process for insurance and repair.

Table 1: Performance Metrics

Method	Accuracy
Manual	0 %
Proposed AI	92.5%

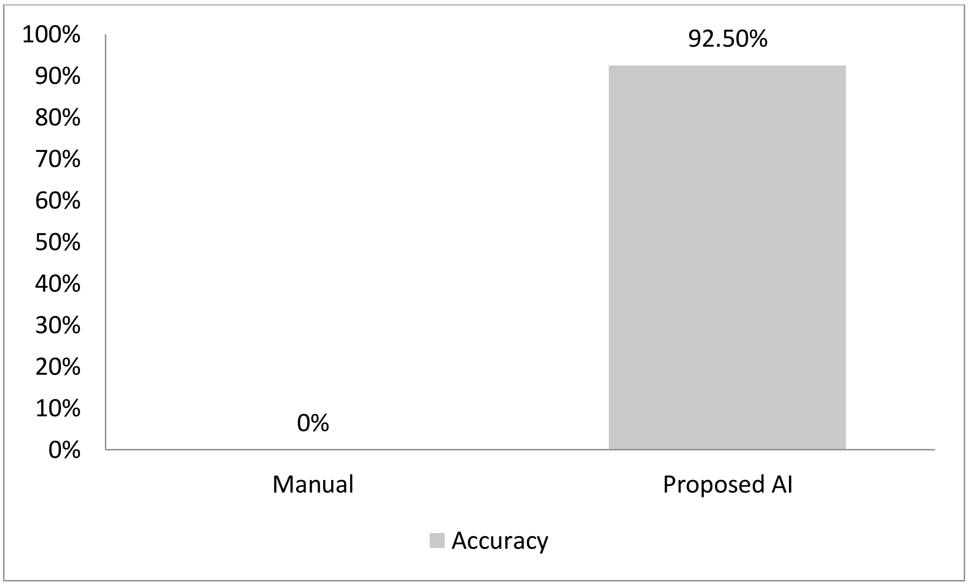

Fig 5: Graph representing Performance Metrics

4.3. Discussion

The damage evaluator proved to be robust in various image variations, entities, and levels of damage. Among its numerous advantages, the model has been proven to be highly accurate in certain cases, particularly in both structured and semi-structured environments, and especially in vehicle images, where damaged areas tend to have more predictable locations. The system performed well in detecting front and rear-end damage during the vehicle inspection. The standardized structural design of such areas is usually homogeneous, and this increases the reliability of feature extraction and damage localization. The fact that the images included high-resolution data and boundaries indicating where certain damage had taken place further helped the CNN identify patterns of the most common damages, including bumper dents, broken headlights, or scratched paint. Consequently, the model achieved maximum estimation accuracy in terms of detecting an element and delivered cost estimates that were close to historical data on repairs.

Unlike this, estimating property damage was more problematic. Pictures involving ruined buildings and infrastructure often feature complicated, unstructured backgrounds with varying scales and shapes of objects. Other noise was introduced due to environmental conditions, such as debris, shadows, and inconsistencies in lighting, which only complicated semantic segmentation and region detection. To illustrate, I required a more advanced level of contextual knowledge to distinguish between cosmetic cracking in the walls and deep structural collapse, which cannot be developed on an image-level basis. Although the system could still perform well in this area, the accuracy was slightly reduced, and the regression model exhibited more variance in terms of cost forecasts. This indicates the necessity to learn more context-related models (and particularly, transformer-based vision systems or 3D reconstruction models) to evaluate large-scale property damage. Altogether, the discussion demonstrates that the proposed AI system is an effective and promising solution for automating damage evaluation. Still, there are areas where it can be improved, such as being able to handle more diverse and unstructured scenes, which would further increase its applicability to even wider domains and in practical use.

5. Conclusion and Future Work

Artificial Intelligence is disrupting conventional businesses at an accelerated rate, and integrating this technology into the insurance industry represents a significant leap toward efficiency, precision, and automation. This paper proposes a selfcontained Artificial Intelligence model for accelerating the damage evaluation of vehicles and properties. Using deep learning, rule-based classification, and regression solutions, the system can identify areas of damage, define the level of severity, and calculate repair costs, based solely on provided images. High-precision visual analysis is possible through the use of Convolutional Neural Networks (CNNs), and visual indicators can be converted into monetary terms using regression models, providing a data-driven alternative to subjective human inspections. The proposed system can significantly reduce the time spent on evaluation compared to traditional approaches, as it is predicted to take up to hours. In contrast, the proposal will take only minutes and be highly accurate at the same time. Further, its automated report generation characteristic gives transparency and standardization, making its output professional and consistent to make to the insurers, repair shops, as well as customers. On the whole, the model presents a scalable and feasible solution that could be utilized in the practical insurance process to enhance the efficiency of operations and customer satisfaction, in general.

Although the already implemented system works quite well in structured and semi-structured scenes, several areas can help increase the system's functionality and scalability. A very promising way to move forward is to incorporate drone footage, which will enable a wider and more comprehensive assessment of property damage, especially when analysing the situation after a disaster. The drones are capable of capturing high-resolution aerial imagery from various angles, which enables the system to gauge the effects of the structures at a large scale when these effects are problematic to record manually by humans Additionally, it is possible to utilise Natural Language Processing (NLP) to expand the system's scope to work with text data on claims, such as customer descriptions of damage or claims. This would enable the cross-validation of visual and textual evidence, thereby enhancing the accuracy of the assessment. Another novel direction is the use of Generative Adversarial Networks (GANs) to generate synthetic damage events for training models. GANs have the potential to increase the robustness and generalization of models by generating realistic but artificial images to supplement the limited or expensive-to-collect labeled data in the real world concerning damage types and intensities. In future versions of the system, it is also possible to consider 3D image reconstruction and multimodal learning in order to introduce a more comprehensive and context-specific assessment tool.

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