CAR DAMAGE SEVERITY ASSESSMENT USING SUPERVISED DEEP LEARNING

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Abstract. The assessment of car damage severity is a critical task in the automotive industry, particularly in insurance claims processing, repairs, and traffic safety analysis. Traditionally, car damage assessment has heavily relied on manual inspections by experts. However, this approach suffers from several limitations, including subjectivity, time consumption, and potential errors, which can lead to inaccurate assessments, delayed insurance claims, and compromised repair processes. This study aims to addresses challenges in accurately assessing car damage severity using deep learning techniques, aiming to overcome limitations associated with manual inspection, such as subjectivity, time consumption, and potential errors. A robust data preprocessing pipeline is implemented using TensorFlow's ImageDataGenerator to prepare and augment the car damage severity assessment dataset, enhancing the model's ability to generalize across diverse data. Once preprocessed, the study continues with 4 supervised deep learning model which are Roboflow, ResNet, EfficientNetV2L and VGG19, with the best performing is EfficientNetV2L with an accuracy of 81%. when trained on 400x400 pixel images for 10 epochs.

Keywords: supervised deep learning, image recognition, transfer learning, car damage, EfficientNet.

1 Introduction

Supervised learning involves understanding the relationship between input variables (X) and an output variable (Y), then using this understanding to predict outcomes for new data. It's a crucial technique in machine learning, especially in handling multimedia data[1]. The supervised deep learning approach is a powerful technique that can be applied to car damage severity assessment. In this approach, a large dataset consisting of labelled examples that corresponds to a specific level of car damage severity (e.g., minor, moderate, severe), is used to train a deep learning model to recognize patterns and features that indicate various damage severity levels.

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The assessment of car damage severity is a critical task in the automotive industry, particularly in insurance claims processing, repairs, and traffic safety analysis. Traditionally, car damage assessment has heavily relied on manual inspections by experts [2]. However, this approach suffers from several limitations, including subjectivity, time consumption, and potential errors, which can lead to inaccurate assessments, delayed insurance claims, and compromised repair processes.

Several similar studies have been conducted on assessing car damage. Among these studies, transfer learning technique shows the most promising result ([3],[4],[5]). More efficient transfer learning applications are chosen in many deep learning studies rather than designing a network from scratch or using an existing network directly because using and modifying a pre-trained CNN model is much easier and faster than training a new CNN model with randomly initiated weights [6].

This paper aims to aid the heavy reliability of manual inspection on car damage and propose an automated and unbiased car damage severity assessment using deep learning techniques.

2 Related Works

2.1 Supervised Deep Learning Techniques

2.1.1 K-Nearest Neighbour

K-nearest neighbour (KNN) algorithm is a type of supervised machine learning algorithm used for classification and regression analysis. It is a non-parametric algorithm that works by finding the K closest data points in the training set to a given test data point and then classifying the test data point based on the majority class of its K nearest neighbours. KNN is known for its simplicity and ease of implementation making it suitable for a wide range of applications, including those where the data is not normally distributed [7].

2.1.2 Support Vector Machine

The Support Vector Machine (SVM) is a supervised learning algorithm used for classification and regression analysis. It is a powerful technique that uses a set of labelled training data to train the classifier and produce input-output mapping functions. The SVM algorithm works by finding the hyperplane that provides the largest minimum distance to the training data, which is used to classify new data points[8].

2.1.3 Convolutional Neural Network

Convolutional Neural Networks (CNN) is a type of deep learning algorithm that has been widely used in image classification and recognition tasks. It is based on the principle of the human nervous system, specifically the brain's neurons, and is formed of artificial neurons that have the property of self-optimization with learning. CNN automate feature extraction from images, eliminating the need for manual feature engineering [9], and excel at handling large datasets making them suitable for complex image classification tasks.

2.1.4 Summary of supervised learning techniques

Table 1. Summary of supervised learning techniques for image recognition

Technique	Advantage	Disadvantage	Best Accuracy
K-Nearest Neighbour	Straightforward and easy to understand and implement	Computational cost increases with a larger dataset	94.9%
Support Vector Machines	Performs well with high-dimensional feature spaces	Computationally expensive, sensitive to hyperparameter choice	100%
Convolutional Neural Network	Automatically learns relevant features from images, identifies features regardless of position, and supports transfer learning	Computationally intensive, may struggle with contextual understanding, sensitive to noisy or distorted data	98.36%

Based on the advantages outlined in the provided information(see Table 1), CNN are the most suitable technique for the project of car damage severity assessment. CNN excel at automatically extracting relevant features from images, irrespective of their position, making them highly effective in identifying and analysing car damage patterns. The parameter sharing property of CNN reduces the number of parameters in the model, making them efficient with limited labelled data.

2.2 Transfer Learning

Transfer learning involves using pre-build models developed for different datasets, as a way to building a new models with different datasets. This is common in machine learning where one model as adapted to another model [10]. Therefore, transfer learning benefits more by utilizing big data systems and larger datasets. Common transfer learning techniques used in machine learning are feature extraction, fine-tuning, domain adaptation, multi-task learning, progressive neural networks, and pre-training and fine-tuning cascades [11]. Most commonly used transfer learning's pre-trained models that trained on image classification or object detection are ResNet, EfficientNet and VGG [11][12].

2.2.1 ResNet

ResNet is recognized as one of the commonly used transfer learning architecture due to its ease of optimization and ability to achieve higher accuracy. It addresses the common issue of vanishing gradients through the use of skip connections in the network [13]. Additionally, ResNet is designed to address the degradation problem in neural networks, where deeper networks often have higher training error rates. To mitigate this, the architecture includes a residual structure that redefines the function of each network layer as the residual function of its input.

2.2.2 EfficientNet

EfficientNet improves model performance by uniformly scaling each dimension using a fixed set of scaling coefficients. Although scaling individual dimensions enhance the model's performance, balancing all dimensions of the network that relatives to the available resources optimizes the overall effectiveness [14]. This is due to the common challenge with CNNs of randomness in adjusting model parameters, such as the number of layers and neurons per layer. With EfficientNet, the model addresses this issue by using a composite coefficient to systematically adjust the network's parameters.

2.2.3 Visual Geometry Group

Visual Geometry Group (VGG) is a straightforward and effective architecture in their capabilities of object detection and classification in photographs. VGG performs well due to the freely available model weights that can be loaded and used for specific tasks [4]. The pre-trained VGG models can be used to address the overfitting issues in small datasets to solve classification, regression, and clustering problems. With VGG16, and VGG19 are the most commonly used VGG models, VGG19 offers better performance compared to other alternatives.

2.3 Car Damage Severity Assessment

Normally the car damage severity assessment is conducted manually by the appointed insurance assessor. This approach suffers from several limitations, including subjectivity, time consumption, and potential errors, which can lead to inaccurate assessments, delayed insurance claims, and compromised repair processes [15]. Consequently, with the increasing rate of car accidents, car insurance companies are losing millions annually due to claims leakage [16] due to error of assessments as one of the factors. Therefore, companies have looked for a way of faster damage assessments.

3 Methodology

3.1 Requirement Analysis

For requirement analysis, A thorough literature review was conducted to extract key information on supervised deep learning techniques and similar systems. The study identified functional requirements, including car image upload, transfer learning model integration, damage severity assessment, results display, user management, and an admin dashboard.

This study employed a dataset sourced from Kaggle that is specifically curated for image of damaged cars. The dataset was catagerorized into three classes: minor, moderate, and severe. The distribution for each of the categories are 452, 463, and 468 images respectively. For data preprocessing, several transformation have been done to the dataset including rescaling, rotation, width and height shift, shear, zoom, and horizontal flip.

Several pre-trained models, including Roboflow, ResNet, EfficientNetV2L, and VGG19 have been evaluated for car damage severity classification (see Table 2). EfficientNetV2L, using transfer learning, performed best with 81% accuracy on 400x400 pixel images for at epochs.

Table 2. Model accuracy summary

Type	Model	Epoch	Image Size	Accuracy
Website Hosted Model Training	Roboflow 2.0 Classification	32	800x800	78.6%
Transfer Learning	ResNet	10	224x224	40%
	EfficientNetV2L	10	400x400	81%
	VGG19	15	400x400	36%

In conclusion, the transfer learning technique emerged as the optimal choice for this project, driven by its superior accuracy, efficiency, and adaptability to our specific requirements. The selected transfer learning model, EfficientNetV2L, characterized by a balance between model size and accuracy, EfficientNetV2L stands out for its ability to efficiently leverage pre-trained knowledge, making it well-suited for our project's objectives.

3.2 System Design

Figure 1 is the system architecture diagram that illustrates the overall structure of the system. It highlights the main components involved and their relationships, providing a comprehensive view of the proposed study's structure and functioning. The diagram shows the representation of web-based module, user interface module, database module, and the report generator module.

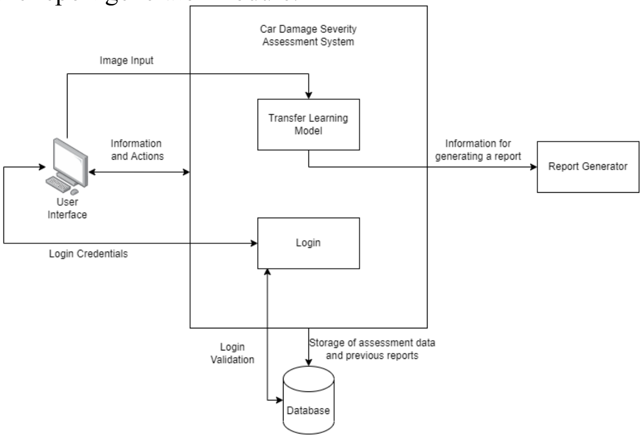

Fig. 1. System Architecture diagram for the proposed study

3.3 Development

The Car Damage Severity Assessment Application Programming Interface (API) uses multiple libraries such as Flask for creating the API, NumPy for numerical operations, TensorFlow for deep learning, and Pillow (PIL) for image processing. The deep learning model for car damage severity assessment is loaded using TensorFlow's function. The model is saved and loaded into the Flask application. The pre-process image opens the image, resizes it to the expected input size of the model (400x400 pixels), converts it to a NumPy array, and applies preprocessing specific to the EfficientNet model.

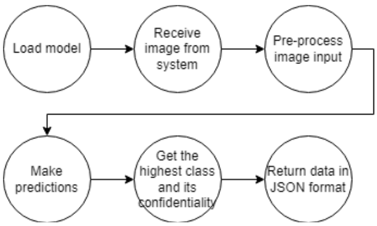

Fig. 2. API Process Flow

The preprocessed image is passed through the loaded model to obtain confidence scores for each class ('minor', 'moderate', 'severe'). The class with the highest score is selected, and the result is formatted into a JSON response. The system then saves the assessment to the database and returns the results to the result page for further actions.

4 Results

4.1 Training and Validation Result

From figure 3, the study obtains the training loss and validation accuracy of EfficientNetV2L by epochs graph. For training loss, it is found that the training loss decreases steadily over the first 12 epochs, reaching a minimum value of around 0.13, and it starts to increase slightly after epoch 12. For validation accuracy, it increases steadily over the first 4 epochs, reaching a peak value of around 0.78, and starts to decrease after epoch 4, reaching around 0.76 at epoch 32.

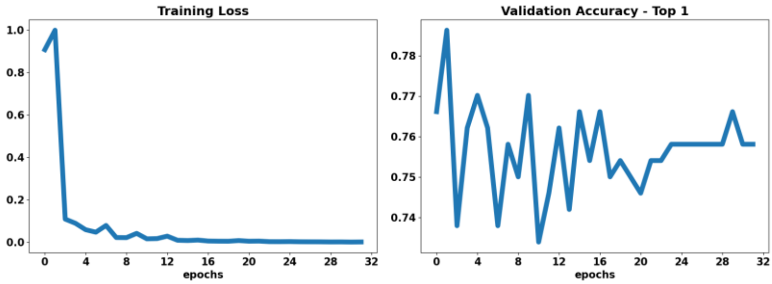

Fig. 3. Training loss and validation accuracy by epochs graph

This study finds that the model is clearly learning from the training data, as evidenced by the decreasing training loss due to transfer learning. However, the model may be overfitting the training data, as the validation accuracy starts to decrease after epoch 4, even though the training loss continues to decrease. This suggests that the model is memorizing the training data too well and is not able to generalize well to unseen data.

Table 3. Result of precision, recall and F1-score of EfficientNetV2L

Class	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Minor	89	84	85	85
Moderate	78	59	65	61
Severe	90	90	82	86

The model is evaluated based on precision, recall, and F1-Score to determine the performance of the model. The model shows a high performance for minor and severe class with both having high precision, recall, and F1-score. However, class moderate is having a moderate performance with a noticeable difference when compare with the other two classes. This indicates that the model struggles more with classyfing moderate class compared to minor and severe damage.

4.2 User Interface and Report

Figure 4 displays the assessment result page, where users will be able to see the result of the car damage severity asessment result. The user-uploaded image appears on the left, while the results are presented in a table with severity (minor, moderate, or severe) and confidence percentage columns. Users have the option to generate a report based on the result or retry the assessment, redirecting them back to the car damage assessment page for further input.

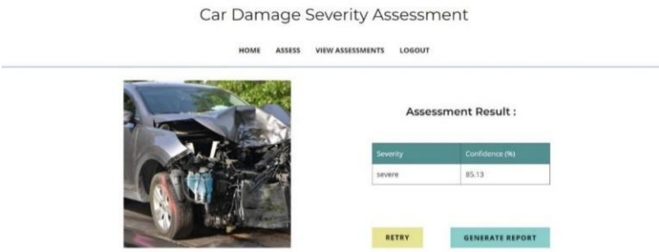

Fig. 4. Assessment Result Page

4.3 Usability Testing Result

Usability testing have been done to this study where users need to evaluate the system. Users can evaluate whether they are strongly disagree, disagree, neutral, agree, and strongly agree. There are five questions that users need to answer. Across all the questions, users seems to give positive feedback regarding the system. This testing suggests a high level of positive feedback regarding the user interface's readability and aesthetic appeal, as well as showing a favourable perception of the system's ease of use.

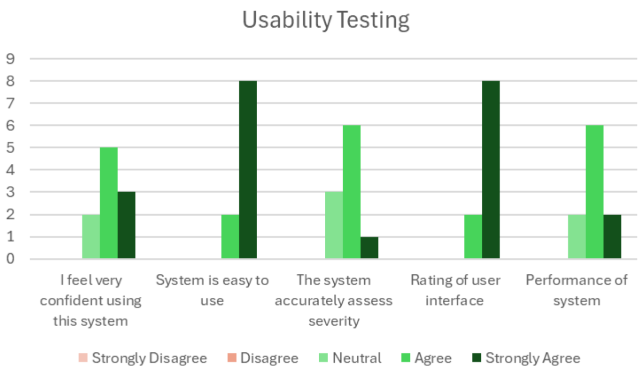

Fig. 5. Usability Testing

5 Conclusion

Car damage assessment has always relied on the knowledge of inspectors who manually evaluate the damaged cars at an accident scene, which could take hours or days long. This study aims to aid the heavy reliability of manual inspection on car damage and propose an automated and unbiased car damage severity assessment using deep learning techniques. CNN was chosen as the most suitable approach, with Efficient2VL transfer learning model is the best performed model with an accuracy of 81% with a balanced dataset. The development of this study faced challenges in model training complexity. Optimizing hyperparameters to balance sensitivity and avoid overfitting or underfitting was crucial. While this study uses balanced dataset, an imbalanced dataset can negatively affect the model's performance. Therefore, a study on handling an imbalanced dataset for this model is recommended as a future study.

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