# OPTIMIZING VEHICLE INSURANCE PROCESSING THROUGH ADVANCED DEEP LEARNING MODELS

**BY**

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## FINAL YEAR DESIGN PROJECT REPORT

This Report Presented in Partial Fulfillment of the Requirements for the Degree of Bachelor of Science in Computer Science and Engineering

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## APPROVAL

This Project titled "Optimizing Vehicle Insurance Processing Through Advanced Deep Learning Models", submitted by Sadman Sadik Khan to the Department of Computer Science and Engineering, Daffodil International University, has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on 14 July, 2024.

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## DECLARATION

We hereby declare that this project has been done by us under the supervision of **Md Sadekur Rahman, Assistant Professor, Department of Computer Science and Engineering, Daffodil International University**. We also declare that neither this project nor any part of this project has been submitted elsewhere for the award of any degree.

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# ABSTRACT

This paper presents a novel method for predicting insurance claims by utilizing artificial intelligence, specifically a deep learning model within the Convolutional Neural Network (CNN) framework. The purpose is to automate and simplify the insurance claims process. The model utilizes computer vision technology to precisely detect and identify car damage, resulting in a substantial reduction in the processing time for insurance claims. The article describes the creation of a specialized dataset consisting of actual photographs of vehicles that have been wrecked. It also assesses multiple deep learning models, ultimately finding that InceptionV3 is the most successful, achieving an accuracy rate of 97%. The suggested AI system seeks to improve the efficiency of claims processing and decrease the need for human evaluation. This would provide a more dependable and efficient method for handling automobile insurance claims after accidents.

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# CHAPTER 1

# Introduction

## 1.1 Overview

In the dynamic landscape of the automotive industry, ensuring the accuracy and efficiency of insurance claim processes is paramount [1]. One of the critical challenges faced by insurance providers is the accurate assessment of vehicle damages, a task traditionally reliant on manual inspection and subjective judgment [13]. To address this issue, the integration of cutting-edge technologies has become imperative.

The advent of Deep Learning, a subset of artificial intelligence inspired by the human brain's neural networks, has revolutionized various industries. Leveraging its capacity for pattern recognition and feature extraction, this research endeavors to enhance the accuracy and speed of vehicle damage assessment, thereby streamlining insurance verification procedures.

Our proposed methodology harnesses the power of convolutional neural networks (CNNs) and image recognition algorithms to analyze images of damaged vehicles. By training the model on an extensive dataset of diverse vehicle damages, the deep learning system learns to discern between different types and severities of damage, allowing for a nuanced and precise evaluation.

This research not only contributes to the optimization of insurance claim processes but also addresses the potential for reducing fraudulent claims. The integration of deep learning techniques promises to provide insurance providers with a reliable and efficient tool for objectively assessing vehicle damages, mitigating the risk of subjective biases and errors associated with human evaluations.

As we delve into the intricacies of our proposed methodology, we aim to showcase the transformative potential of Deep Learning in the realm of vehicle damage insurance verification. By combining technological innovation with real-world application, this research seeks to propel the insurance industry towards a more accurate, transparent, and expedited claims processing system.

## 1.2 Background and Present State

**Background:**

In recent years, the insurance industry has witnessed significant transformation due to technological advancements, particularly in the realm of vehicle insurance. Traditional processes, often manual and time-consuming, have increasingly become automated and more efficient, thanks in part to the integration of advanced computational technologies. Vehicle insurance, a critical component of the automotive industry, involves assessing risk, determining premiums, processing claims, and managing customer relationships. These tasks, historically handled by human assessors, are ripe for enhancement through artificial intelligence (AI) and machine learning (ML).

Deep learning, a subset of machine learning characterized by algorithms inspired by the structure and function of the brain called artificial neural networks, has shown particular promise. It has the capability to process vast amounts of data, learn complex patterns, and make informed decisions with minimal human intervention. This technology's application in vehicle insurance can potentially lead to more accurate risk assessment, faster claim processing, personalized insurance offerings, and overall improved customer service.

**Present State:**

The application of deep learning in vehicle insurance is part of a broader trend towards digital transformation in the industry. Current state-of-the-art implementations primarily focus on automating the claims processing and fraud detection processes. For instance, convolutional neural networks (CNNs) are being employed to analyze images from car accidents to assess damage levels automatically. This application not only speeds up the claims process but also reduces the likelihood of human error and bias.

Similarly, deep learning models are being used to detect patterns indicative of fraudulent claims. By analyzing historical data, these models can identify anomalies and flag potential frauds much faster than traditional methods, thereby saving significant costs for insurance companies. Moreover, predictive analytics using deep neural networks (DNNs) are being developed to better forecast risks and personalize insurance premiums based on individual driving behaviors and histories.

Despite these advancements, there are ongoing challenges, including data privacy concerns, the need for large labeled datasets for training models, and the interpretability of deep learning decisions. Moreover, while the adoption of these technologies is growing, the integration of deep learning into existing insurance systems requires careful consideration of regulatory and ethical issues to ensure fair and equitable treatment of all customers.

In conclusion, the ongoing evolution of deep learning applications in vehicle insurance promises substantial benefits but also poses significant challenges that must be addressed to fully leverage this technology in enhancing the efficiency and effectiveness of insurance processing.

### 1.3 Problem Statement

In the insurance industry, processing claims for vehicle damage is a common and most essential task [2]. With the advancement in AI and Computer Vision, the users can settle the claims online instantly by uploading the images of the damaged car with the insurance company.

Now, insurance companies face the constant challenge of identifying fraudulent claims [1]. It's a common practice for the users to submit the fraudulent images as a part of the claim settlement process. This brings out the threat/challenge to the insurance companies to identify the fraudulent claims which leads to significant financial losses [4].

Fraudulent claims often involve exaggerating the extent of damage or submitting false claims altogether [3]. In this problem, we will focus on the first type of problem exaggerating the extent of damage. To mitigate these losses and maintain the integrity of their operations, insurance companies must develop effective methods to flag out these claims most accurately and efficiently.

The purpose of this paper is to develop a robust and high-performance model for classifying an image of a car into different types of damages automatically with the help of computer vision techniques. By accurately identifying the damages, the insurance company can assess the legitimacy of the claim and make informed decisions regarding payouts.

## 1.4 Objectives

The primary objective of this project is to develop a highly efficient and accurate model utilizing computer vision techniques to automatically classify images of damaged vehicles into different types of damages. By achieving this objective, we aim to address the following key goals:

1. **Automate vehicle damage verification:** Reduce reliance on manual inspection for insurance claims, leading to faster processing and reduced costs.

2. **Minimize fraudulent claims:** Identify potential fraudulent claims by detecting inconsistencies or manipulated images.

3. **Improve accuracy and consistency:** Leverage deep learning's ability to learn complex patterns for more accurate damage detection and classification compared to human assessment.

4. **Enhance customer experience:** Offer a faster, more convenient claim process for insured individuals.

By accomplishing these objectives, this project aims to contribute to the ongoing evolution of the insurance industry, fostering a more secure and efficient environment for both insurance companies and policyholders in the digital age.

## 1.5 Scope and Limitations

**Scope Inclusions:**

- Damage detection and classification for common vehicle damage types (e.g., scratches, dents, broken windows).
- Integration with standard image formats.
- Model training on a diverse dataset of vehicle images with varying damage levels.

- Basic data visualization tools for damage visualization.

**Scope Exclusions:**

- Advanced damage assessment (e.g., estimating repair costs).
- Integration with specific insurance company claims systems (requires additional customization).
- Multi-lingual support.
- Fraud detection capabilities.
- Advanced user management and access control features.

### 1.6 Report Organization

Our report consists of three chapters, each covering different aspects of the project.

Chapter 1 provides an overview, including sections such as 1.1 Overview, 1.2 Background and Present State, 1.3 Problem Statement, 1.4 Objectives, 1.5 Scope and Limitations, 1.6 Report Organization, and 1.7 Summary.

In Chapter 2, I delve into the discussion with sections like 2.1 Overview, 2.2 Related Work, 2.3 Comparison between existing works, 2.4 Open Issues and 2.5 Summary.

The research methodology, along with its subsections, is presented in Chapter 3, which includes 3.1 Overview, 3.2 Proposed Methodology, 3.3 Software Requirement, 3.4 Project Management and Financial Analysis and 3.5 Summary.

In chapter 4, I discuss about the implementation, including 4.1 Overview, 4.2 Model Train, 4.3 Model Evaluation and 4.4 Summary.

In chapter 5, I discuss about the experimental result, including 5.1 Overview, 4.2 Experimental Results, 5.3 Performance Analysis and 5.4 Summary.

The impact on society, environment and sustainability, along with its subsections, is presented in Chapter 6 which includes 6.1 Impact on Life, 6.2 Impact on Society & Environment, 6.3 Ethical Aspects, 6.4 Sustainability Plan and 6.5 Summary.

In Chapter 7, I delve into the discussion with sections like 7.1 Conclusions, 7.2 Further Suggested Works and 7.3 Limitations.

Throughout each section, I have created scenarios to support and enhance our research.

## 1.7 Summary

"Optimizing Vehicle Insurance Processing Through Advanced Deep Learning Models" endeavors to revolutionize the insurance sector by introducing a cutting-edge solution that harnesses the power of deep learning. The project aims to address the limitations of manual assessment, bringing efficiency, accuracy, and fraud prevention to the forefront of the insurance verification process. Through advanced neural network architectures and meticulous methodology, this initiative aspires to redefine the landscape of vehicle damage assessment, ushering in a new era of technological innovation within the insurance industry.

# CHAPTER 2

# Literature Review

## 2.1 Overview

The integration of deep learning techniques in various domains has revolutionized the way complex problems are approached and solved. In the realm of insurance, particularly in the verification of vehicle damage claims, the application of deep learning has garnered significant attention. This literature review explores the existing body of knowledge and research pertaining to the utilization of deep learning methods for the verification of vehicle damage in the context of insurance claims.

As the automotive industry continues to evolve with advancements in technology, the complexity of assessing vehicle damages has increased. Traditional methods of inspection and evaluation are often time-consuming, prone to errors, and may lack accuracy in identifying subtle damages. Deep learning, a subset of artificial intelligence, offers a promising solution by enabling machines to learn and automatically extract features from large datasets, allowing for more efficient and precise analysis of vehicle damages.

The literature review aims to provide a comprehensive understanding of the current state of research in this field, highlighting key methodologies, challenges, and advancements. By delving into relevant studies, methodologies, and innovations, this review seeks to establish a foundation for the proposed research on "Vehicle Damage Insurance Verification using Deep Learning." Through the synthesis of existing knowledge, we aim to identify gaps in the literature and lay the groundwork for the development of an effective and robust deep learning-based system for automating the verification process in vehicle damage insurance claims.

In the subsequent sections, we will explore the key concepts and approaches employed in existing studies, examining the strengths and limitations of different methodologies. Additionally, we will analyze the impact of deep learning on enhancing the accuracy of damage assessment, streamlining claims processing, and ultimately contributing to the overall efficiency and fairness of the insurance industry. This literature review serves as a vital precursor to the proposed research, guiding the investigation into the development of innovative solutions for the challenges posed by vehicle damage insurance verification

## 2.2 Related Works

Machine learning models based on feature engineering have made great strides in motor insurance fraud detection in recent years. The authors of [4] create an Auto Insurance Multi-modal Learning (AIML) framework by modifying our knowledge-based approach to accommodate both computer vision and natural language processing techniques. Subsequently, they conduct tests to investigate the improvement in model performance with multi-modal data compared to baseline model with structural data only, and then utilize AIML to detect fraud behaviour in vehicle insurance cases using data from real scenarios. Within AIML are incorporated a visual data processing framework and a self-designed algorithm called the Semi-vehicle Feature Engineer (SAFE) for analysing vehicle insurance data. The findings indicate that as compared to models that solely rely on structural data, AIML significantly enhances the model's effectiveness in identifying fraudulent activity.

Damage to vehicles is turning into a growing liability for shared mobility providers. Due to the volume of handovers between drivers, a precise and quick inspection system that can identify minor damages and assign them to the appropriate damage category is required. In order to solve this, a damage detection model is created in [5] to find vehicle damages and categorize them into twelve groups. To maximize the detection performance, a variety of deep learning algorithms are employed, and the impact of various transfer learning and training approaches is assessed. After being trained on over 10,000 damage photos, the final model can reliably identify minor defects in a variety of environments, including wet and dirty ones. Comparable performance is achieved by the model, according to a performance review conducted with domain experts. Furthermore, a specifically constructed light street is used to evaluate the model, revealing that intense reflections impede the detection performance.

An approach based on picture recognition can be used to detect damage on autos. Car insurance companies, automobile rental companies, and auto repair agencies would find this technique for identifying and calibrating external damage on a car to be of great utility. Licensing firms and used car sellers have always faced difficulties with reporting car damage and calculating penalties. The use of deep learning and neural networks to construct an architectural model of Mask R-CNN that can estimate the car's damaged surface area is presented by the authors in [7]. Our approach for precise instance segmentation of the damaged auto parts is a deep feature prediction network. In order to address the issues that the used car industry and automobile rental companies are facing, this study is an extension of business technology to detect and quantify car scratches. It will help companies cut out intermediaries and open the door for a more impartial pricing and insurance structure in the car dealership industry. The Mask-RCNN model obtains a fairly high accuracy of about 93%. The suggested research makes use of a customized new dataset that consists of photos of damaged automobiles from diverse scenarios with exact labelling and annotation for image segmentation.

Applications for the identification and tracking of automobiles involved in auto insurance claims are significant in the area of intelligent loss assessment. In [8], a convolutional neural network is used in deep learning to build a model of vehicle recognition and direction determination based on ResNet-101+FPN backbone network and RetinaNet. Next, using the labelled data set, the model is tested and trained. The prediction accuracy of the model is comparatively excellent; it achieves 98.7% for vehicle detection and 97.2% for the five directions of frontal, lateral-frontal, lateral, lateral-back, and back determination.

In order to project future claims, traditional claim forecasting techniques try to fit the frequency and severity of claims with a given probability distribution function. A novel method for predicting insurance claims is provided by the study [9]. In order to predict the average (mean) insurance claim per insured car per quarter, they first add two novel sets of variables: weather and automobile sales. Secondly, they use a variety of machine learning methods, including SVM, Decision Trees, Random Forests, and Boosting. Lastly, they determine which factors have the biggest effects on predicting insurance claims. Their dataset, which covers the years 2008 through 2020, is derived from the automotive portfolio of an insurance provider with operations in Athens, Greece. They discovered evidence that the minimum temperature of Elefsina, one of the Athens weather stations, with a 3-quarter lag, and new car sales with a 3-quarter and 1-quarter lag are the three most telling factors. The models that performed the best were XGboost ran on the 15 most relevant variables and Random Forest with limited depth.

In [10], the authors employed an enhanced Mask R-CNN approach to automatically detect, identify, and classify car damage areas in traffic events. This method provides a major research benefit of object detection. They combined deep learning, mask R-CNN, instance segmentation, and transfer learning to recognize and categorize an image of a damaged car. Furthermore, an automated web-based claim estimator has the capability to receive user-supplied images and autonomously ascertain the location and extent of the damage. In addition, three distinct pre-trained models were employed to facilitate rapid convergence: inception ResNetV2, VGG-16, and VGG-19. Lastly, based on the three pre-trained models, comparative performance evaluations use a variety of evaluation metrics, including accuracy, precision, recall, F1 score, loss function, and confusion matrices. The study's goal of automatically locating and classifying automotive damage is achieved by the suggested method, which not only recognizes damaged vehicles but also locates them and assesses their severity level, according to the empirical data. The results show that using Mask-RCNN with Inception ResNetV2 that has already been trained performs better than the other models in all areas related to detection, localization, and severity-damaged performance.

The above studies have revealed that though there were a lot of research works have been done on vehicle damage detection, none of this was based on Bangladesh and their there is still scope to improve the performance of model. Our research aims to address these issues to contribute in this trendy field.

### 2.3 Comparison between existing works

TABLE 1: COMPARATIVE ANALYSIS WITH PREVIOUS WORK

| SL No | Author Name | Used Algorithm | Best Accuracy with Algorithm |
|---|---|---|---|
| 1. | Njeru [10] | AdaBoost, XGBoost, NB, SVM, LR, DT, ANN, RF | AdaBoost/XGBoost (84.5%) |
| 2. | Rudra et al. [11] | Mask-RCNN | Mask-RCNN (93%) |
| 3. | Qaddour & Siddiqa [5] | Mask R-CNN, VGG-16, VGG-19, Inception-ResNetV2 | Inception-ResNetV2 (92%) |

| | | | |
|---|---|---|---|
| 4. | Waqas et al. [15] | MobileNet, Transfer Learning | MobileNet (95%) |
| 5. | Sarath P et al. [8] | CNN, VGG-16, Transfer Learning, Ensemble Learning | Transfer and Ensemble Learning (89.5%) |
| 6. | Kalpesh Patil et al. [14] | CNN, Autoencoder, Transfer Learning, Ensemble Learning | Transfer and Ensemble Learning (89.5%) |
| 7. | R. Singh et al. [20] | Parts MRCNN,<br>Parts PANet, Ensamble (Parts MRCNN + PANet), Damage MRCNN | Ensamble 38%<br>Damage MRCNN 40%<br>mAP Score |

### 2.4 Open Issues

Optimizing vehicle insurance processing through advanced deep learning models involves several challenges that must be addressed to ensure the efficiency and effectiveness of these technological solutions. Here are some of the key challenges:

1. Data Quality and Availability:

- Variability in Data: Vehicle insurance claims data can vary greatly in terms of quality, format, and detail depending on the source. Ensuring consistency across diverse datasets is challenging.
- Incomplete Data: Claims often have missing or incomplete information, which can hinder the training of deep learning models.

2. Model Complexity and Scalability:

- High Dimensionality: Insurance claims processing involves a vast amount of data with numerous features, which can complicate model design and training.
- Scalability: Developing models that are scalable and can handle increasing volumes of claims without a loss in performance is challenging.

3. Integration with Existing Systems:

- System Compatibility: Integrating advanced deep learning models into existing insurance processing systems without disrupting current operations.
- Technology Adoption: Resistance to adopting new technologies can be a significant hurdle in some traditional insurance companies.

4. Real-Time Processing:

- Speed of Processing: Implementing models that can process claims in real-time or near-real-time to expedite decision-making.
- Dynamic Adaptation: Models must be capable of adapting to new patterns in claims data as they emerge.

5. Regulatory Compliance and Data Privacy:

- Compliance: Ensuring that the models comply with all relevant laws and regulations, including those related to data privacy and consumer protection.
- Ethical Concerns: Addressing potential biases in AI decision-making processes to prevent unfair treatment of claimants.

6. Accuracy and Reliability:

- Error Rates: Minimizing false positives and false negatives in claim predictions to avoid wrongful rejections or approvals.
- Generalization: Ensuring the model performs well not just on training data but also on unseen, real-world data.

7. Costs of Implementation:

- Infrastructure Costs: The high costs associated with developing, training, and maintaining sophisticated models.
- Skill Requirements: The need for skilled personnel who can develop, deploy, and maintain these advanced models.

Addressing these challenges requires a well-planned strategy involving technological, organizational, and regulatory considerations to fully leverage the benefits of deep learning in optimizing vehicle insurance processing.

## 2.5 Summary

The literature review section of the research on "Vehicle Damage Insurance Verification using Deep Learning" delves into the existing body of knowledge related to both vehicle damage assessment and the application of deep learning techniques in insurance verification processes. The review begins by examining traditional methods of assessing vehicle damage, highlighting their limitations and emphasizing the need for more accurate and efficient solutions. Subsequently, the literature explores the emergence and evolution of deep learning in various domains, particularly its successful applications in image recognition, object detection, and pattern recognition.

The review then narrows its focus to studies and projects specifically related to vehicle damage assessment using deep learning approaches. It discusses relevant research methodologies, such as convolutional neural networks (CNNs) and other deep learning architectures, that have shown promise in accurately identifying and quantifying damage in images of vehicles. The section also addresses the challenges and potential pitfalls associated with deploying deep learning models in real-world insurance verification scenarios, including issues related to data variability, model interpretability, and ethical considerations.

Throughout the literature review, the research establishes a foundation for the current study by synthesizing key findings and identifying gaps in the existing literature. By critically analyzing the strengths and limitations of previous research, the review sets the stage for the subsequent sections of the paper, emphasizing the need for advancements in vehicle damage insurance verification through the integration of deep learning techniques.

# CHAPTER 3
# Methodology

## 3.1 Overview

In the realm of modern technology, the integration of advanced systems to streamline and enhance various processes has become imperative. One such critical domain is the insurance industry, where the efficient verification of vehicle damage claims plays a pivotal role in ensuring fair and accurate compensation. The advent of deep learning techniques has opened up new possibilities for automating and optimizing these verification processes.

This section provides a comprehensive overview of the Methodology, Requirement Analysis, and Design Specification for the development of a cutting-edge system titled "Vehicle Damage Insurance Verification using Deep Learning." The primary objective of this initiative is to leverage the power of deep learning algorithms to accurately assess and verify vehicle damage claims, thereby expediting the insurance claims process and minimizing fraudulent activities.

The methodology employed in the development of "Vehicle Damage Insurance Verification using Deep Learning" focuses on leveraging state-of-the-art deep learning techniques to automate and improve the accuracy of the vehicle damage assessment process. This section provides an insightful overview of the strategic steps and approaches undertaken to ensure the successful integration of deep learning into the insurance verification workflow.

## 3.2 Proposed Methodology

In this section, we are going to write the step by step proposed methodology for this work which includes data collection, data cleaning, data preprocessing, model training, model evaluation. Figure of the overall methodology is given below and every step of the methodology is further discussed in the following subsections.

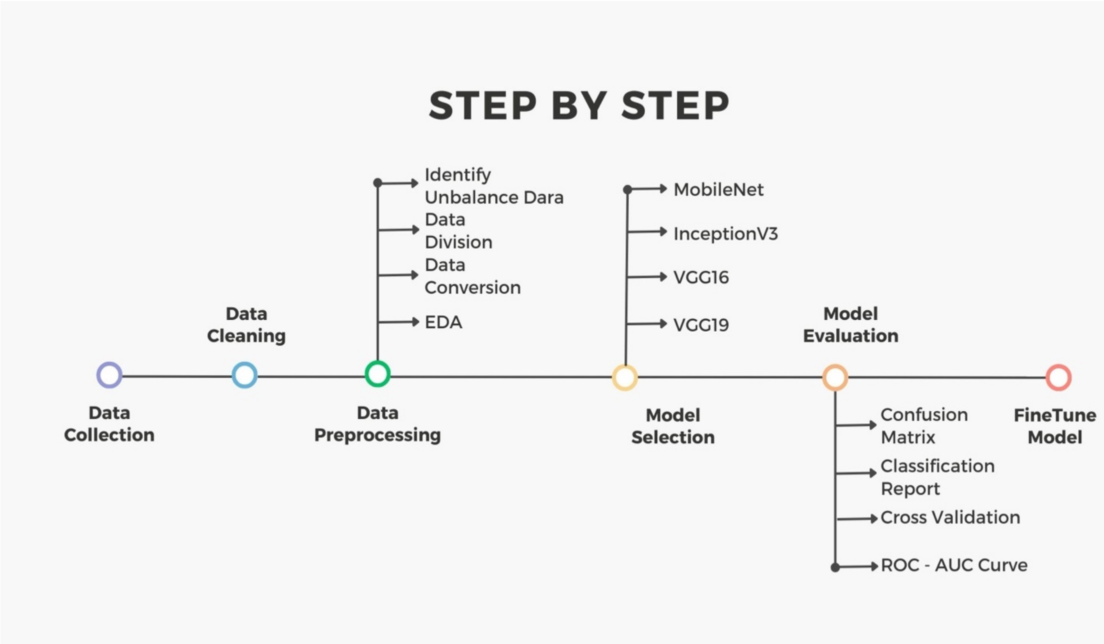


Figure 3.2.1: Proposed Methodology

### 3.2.1 Data Collection

Data Collection is the most difficult part of our project. As part of our project, we have visited and met with an insurance company. The purpose is to get a clear idea of insurance process in Bangladesh. This meeting will guide us in determining the specific type of data we need to use for our analysis.

Data collection was completed by visiting a number of automobile shops situated in Dhaka, Bangladesh. Direct field collection was undertaken to ensure the inclusion of real-world variations and environmental factors in the dataset. The proceeding included capturing pictures with various mobile devices, most of which use a 54-megapixel primary camera for capturing images. The pictures were captured using stands to acquire the most stable images. Altogether 5121 images were collected for five different damage categories namely "Crack", “Scratch”, “tire flat”, “glass shatter”, and “lamp broken”.

In our dataset we have total 5121 raw images which categories in 5 classes. Frequency of images are shown in Table 2 and sample images of different classes are shown in Figure 3.2.2.

TABLE 2: FREQUENCY OF IMAGES

| Class | Number of Images |
|---|---|
| Scratch | 2349 |
| Glass Shatter | 1185 |
| Lamp Broken | 882 |
| Tire Flat | 534 |
| Crack | 171 |

Crack

Glass Shatter

Lamp Broken

Scratch

Tire Flat

Figure 3.2.2: Sample Dataset

### 3.4.2 Data Cleaning & Preprocessing

Primarily collected images were huge in number and consisted of unnecessary, blurry, or overexposed images, which might cause trouble while training the model. To increase the precision of the dataset, these images were removed from the primary dataset. The images captured from the open scenario were at a high resolution of 1080x2400 pixels, which is suitable for use in our testing models. We rescaled the images using (1/255) which converts the pixels of the images from the (0, 255) range to a range of (0, 1) so that the images contribute more evenly in case of loss. The preprocessed images are kept at a resolution of 448x448 pixels. Also, for some of the images that consisted of some noisy portions but not in a major way, de-noise procedure was applied to them specifically.

### 3.2.3 Data Split

In total, 5121 images classified into five categories are stored in local storage as well as in cloud storage (Google Drive) for future usage. All of these images are used for training, testing and validation the model. For training we used 4096 images. In the same procedure of preparing the training dataset, to avoid biasing the model, the testing dataset and validation dataset are generated separately by splitting the training dataset. The testing dataset portion consists of 513 images and the validation dataset portion consists of 512 images for the model to predict.

### 3.2.4 Model Selection

**VGG16:**

Given its track record of success in image classification tasks, we aim to use the VGG16 architecture for the detection of damaged parts of vehicles. The deep convolutional neural network (CNN) architecture VGG16 is renowned for its exceptional performance on the ImageNet dataset and its ease of use. It can capture complex patterns and characteristics in images thanks to its 16-layer architecture, which consists of 3 fully linked layers and 13 convolutional layers. VGG16's deep architecture is well-suited to extract hierarchical characteristics from leaf images, enabling accurate disease identification, given the complexity and diversity of damage parts. Furthermore, the pre-trained weights of VGG16 on extensive datasets offer a useful starting point, enabling fine-tuning on the particular dataset of photos of damaged parts, which can improve the model's capacity to pick up pertinent damage-related characteristics. Overall, VGG16 is an attractive option for the deep learning job of verification of damage insurance because of its outstanding performance, deep architecture, and availability of pre-trained weights.

**VGG19:**

VGG19 is a strong option for the deep learning-based task of detecting damaged parts because of its intricacies and track record of success in picture classification. An enhanced version of VGG16, called VGG19, has 19 layers—16 convolutional layers and 3 fully linked layers—that together enable a more intricate and in-depth feature extraction procedure. With this depth, the network can potentially improve the model's capacity to distinguish between good and damaged parts by capturing a wider variety of characteristics and patterns found in car images. Furthermore, VGG19 keeps the original VGG architecture's simplicity intact, which makes it simpler to comprehend and use. Furthermore, training damage vehicle datasets with pre-trained weights from VGG19 on large-scale datasets can be a useful first step, hastening model convergence and possibly enhancing performance. As a result, VGG19 sticks out as a solid contender for damage detection in insurance process since it provides a blend of architectural complexity, ease of use, and transfer learning abilities that are in line with the demands of the task.

**MobileNetV2***:*

Because of its effectiveness and small architecture, MobileNetV2 is a great option for identifying damage to the car image. Because of its lightweight architecture, MobileNetV2 can analyze leaf pictures quickly, which makes it appropriate for real-time applications and contexts with limited resources. It minimizes computing needs while maintaining excellent feature extraction with depth wise separable convolutions. For training on smaller datasets, such as those found in agricultural applications, this efficiency is beneficial. By using transfer learning, MobileNetV2's features may be adjusted to provide precise damage identification on the particular damage vehicle dataset. All things considered, MobileNetV2 is a strong contender for this purpose because of its effectiveness and versatility.

**ResNet50:**

Because of its deep architecture and exceptional performance in image classification tasks, ResNet50, also known as Residual Network, is a great option for identifying damages in a damaged photo. By including skip connections, ResNet50 mitigates the vanishing gradient issue and makes it easier to train very deep networks, allowing for the effective training of models with hundreds of layers. This architecture improves the model's capacity to distinguish between a good and damaged car by making it easier to extract complex characteristics from vehicle photos. Moreover, large-scale dataset pre-trained ResNet50 models provide a solid foundation, allowing for effective fine-tuning on the damage vehicle dataset. ResNet50 is a potent tool for precise disease diagnosis in agricultural settings because of its deep architecture and demonstrated efficacy.

**InceptionV3:**

Inceptionv3 is a powerful image recognition model built on the concept of convolutional neural networks. It excels at helping with object recognition and picture analysis in particular. It is the third version of Google's Inception architecture, which was first made famous during the ImageNet picture categorization competition. The architecture of Inceptionv3 achieves a compromise between efficiency and comprehensive analysis. This is made possible by methods like as factorized convolutions and carefully positioned classifiers, which result in a model with fewer than 25 million parameters, which is a major advancement over previous models. The architecture of Inceptionv3 serves as the basis for a large number of computer vision applications. It is frequently utilized in a pre-trained state, making advantage of the enormous quantity of picture data required for training to do tasks like object categorization in new datasets.

### 3.4.6 Model Evaluation

The models will be evaluated using various metrics such as precision, accuracy, recall, and F1 score. These metrics provide a comprehensive understanding of each model's performance.

The performance of the models was evaluated using Precision, Recall, F1-score, and Accuracy.

Precision is a metric that measures the proportion of correctly identified positive instances among all predicted positive instances, calculated as follows:

$$Precision = \frac{True\ Positives}{TruePositives + FalsePositives}$$

Recall, also known as sensitivity or the true positive rate, measures the proportion of actual positives correctly identified, calculated by:

$$Recall = \frac{True\ Positives}{TruePositives + False\ Negetives}$$

The F1-score is a statistical measure that combines precision and recall, providing a balance between the two by calculating their harmonic mean:

$$F1 = 2 * \frac{Precesion\ and\ Recall}{TruePositives + FalsePositives}$$

Comparing models: I use appropriate evaluation metrics to compare the performance of different models. It helps determine which pattern works best for a particular task and provides guidance on pattern selection and implementation.

**Proposed Model Architecture**

A bottleneck with a depth wise distinct convolution with residuals serves as the basic building block. InceptionV3 may be considered the head by utilizing exchange learning, whereas other layers can be considered the tail for specific classification assignments. Here, the venture employs an InceptionV3 variant whose input could be a 448 by 448 picture. The show at first changes over the inputs compressed low-dimensional representation to tall measurements some time ago, recently sifting it employing a fast profundity shrewd combination. After that, a straight convolution is utilized to extend the highlights back to a low-dimensional shape. Figure 3.2.3 shows the InceptionV3 building piece with the subtle elements of change counting, bottleneck input, yield, and operations.

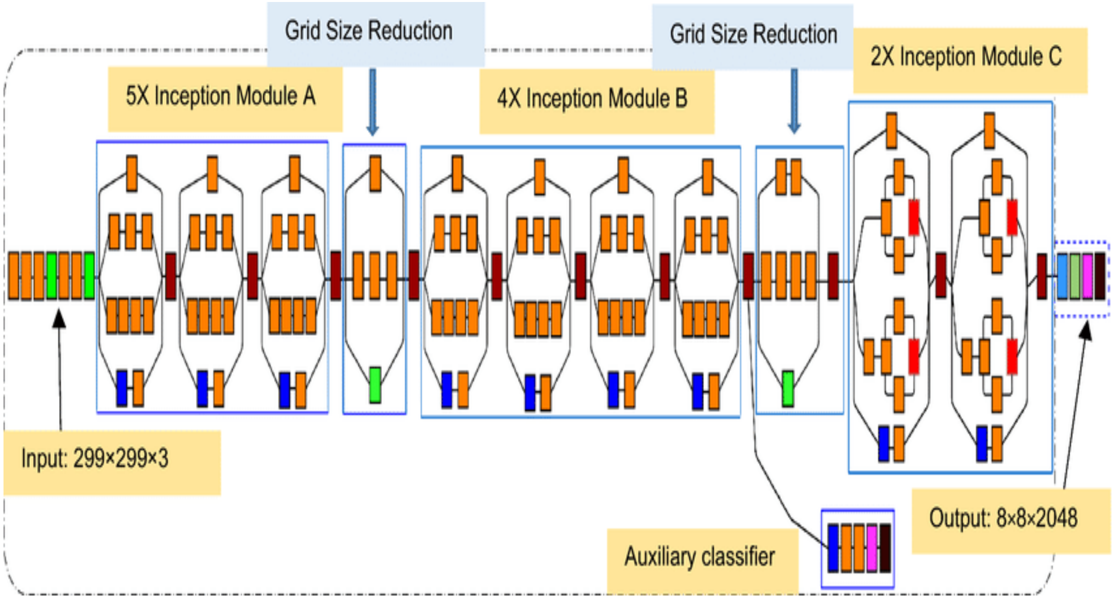


Figure 3.2.3: Architecture of the Proposed Model

### 3.3 Software Requirement

A powerful computer, graphics processing unit (GPU), and other tools are essential for a deep learning model.

The tools required for this model are described below:

TABLE 3: LIST OF THE REQUIREMENTS

| Hardware and software | Development Tools |
|---|---|
| Intel i5 3600, 6-core processor | Windows 10 |
| Ram 8 GB | Python 3.9 |
| Google Colab, Jupyter Notebook | TensorFlow |
| SSD 256 GB | Flask |

### 3.4 Project Management and Financial Analysis

- Project Objectives:
  - A. To develop a web-based application for verify vehicle damage
  - B. To make short & easy the insurance claims process
- Project Timeline:

A. Phase 1: Project Planning and Research (1-2 weeks)
B. Phase 2: Established Collaboration with Professionals (4-5 weeks)
C. Phase 3: Reference Paper Collection (4-6 weeks)
D. Phase 4: Paper Review (4-6 weeks)
E. Phase 5: Data Collection (8-10 weeks)
F. Phase 6: Data Analysis (4-6 weeks)
G. Phase 7: Data Preprocessing (3-4 weeks)
H. Phase 8: Model Implement (3-4 weeks)
I. Phase 9: Model Evaluation (On Going)
J. Phase 10: Prototype Design (3-4 weeks)
K. Phase 11: Front End Development (On Going)
L. Phase 12: Back End Development (Up Coming)
M. Phase 12: Deployment & Testing (Up Coming)
N. Phase 14: Post-Launch & Marketing (Up Coming)

The project management timeline is given below:

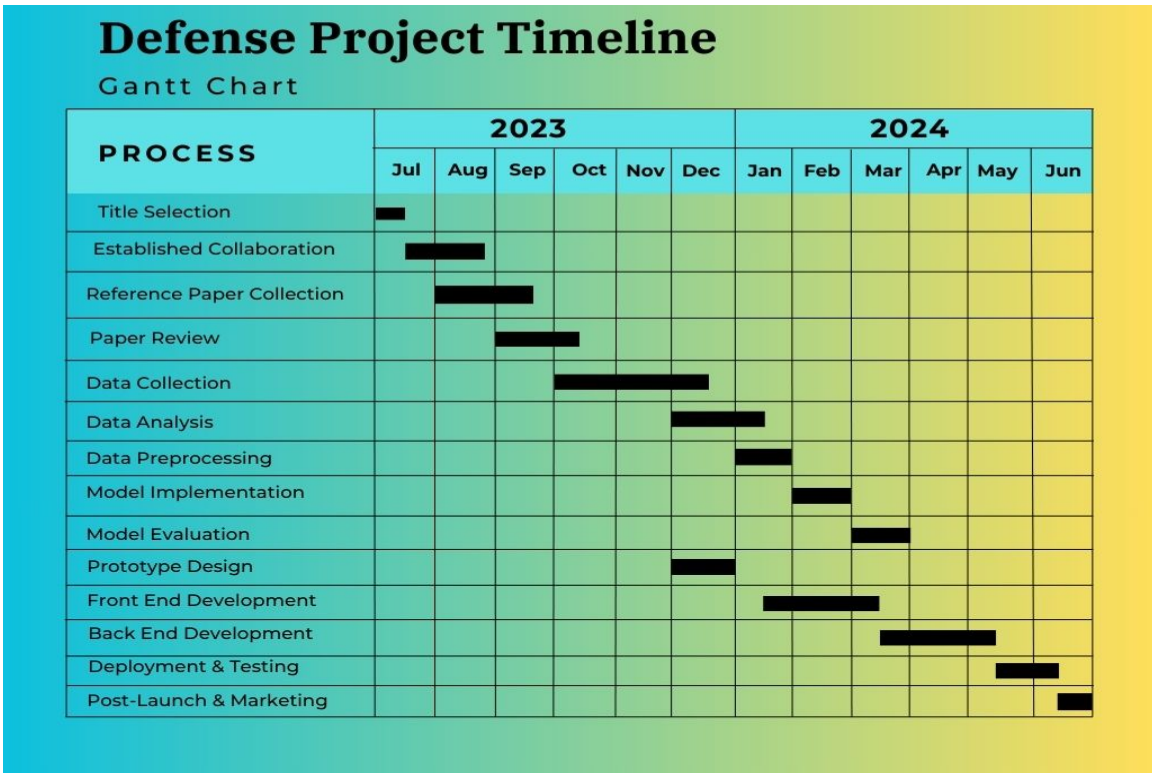


Figure 3.4.1: Gantt Chart for Project Timeline

- Resource Planning:

A. Equipment and Tools:

- Development and Testing Servers
- High-performance Computers for Development Team Design Software (e.g., Adobe Creative Suite)
- Collaboration Tools (e.g., Slack, Trello, or project management software)
- Version Control System (e.g., Git)
- Testing Tools (e.g., Selenium for automated testing)

B. Software and Technologies:

- Front-End Technologies (e.g., HTML, CSS, JavaScript, React or Angular)
- Back-End Technologies (e.g., Node.js, Django, Flask, or Ruby on Rails)
- Database Management System (e.g., MySQL, PostgreSQL, or MongoDB)
- Server Hosting (e.g., AWS, Azure, or Google Cloud)
- Security Software and SSL Certificates

C. Data and Content:

- Product Images: Obtained through agreements with suppliers
- User Documentation: Prepared by the technical writing team

D. Training and Skill Development:

- Ensure that the development team has the necessary training and skills in web-based application development, security, and database management.
- Provide additional training on specific technologies and tools as needed.

● Risk Management:

SWOT analysis involves assessing the Strengths, Weaknesses, Opportunities, and Threats of a project. Here's a SWOT analysis for the vehicle damage insurance:

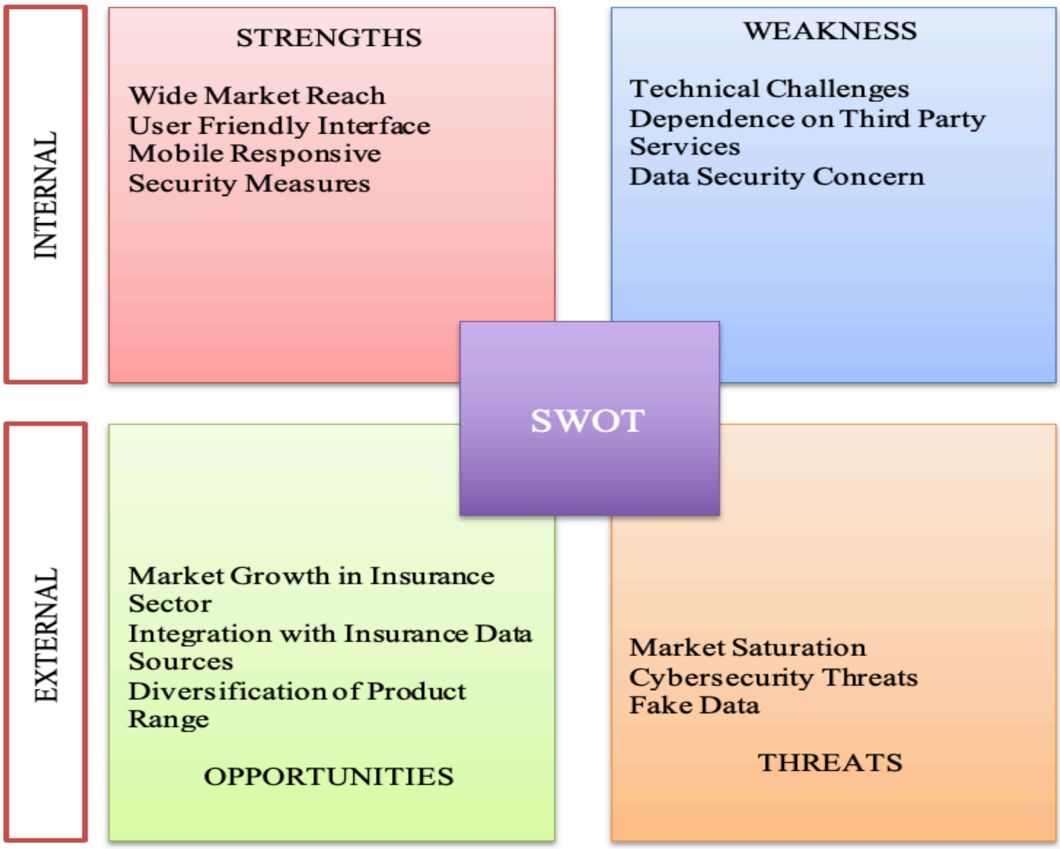


Figure 3.4.2: SWOT Analysis

- Communication Plan:

  A. Stakeholder Meetings:

     Purpose: Update stakeholders on project requirements gathering progress and gather feedback.

     Participants: Team members, and stakeholders.

     Frequency: Bi-weekly or as specified in the project plan.

  B. Change Control Meetings:

     Purpose: Discuss and approve any changes to the project scope or requirements.

     Participants: Supervisor and team members.

Frequency: As needed when change requests arise.

**Finance:** The cost table is given below:

TABLE 4: ESTIMATED COST FOR THIS PROJECT

| SN | Components | Estimated Cost (BDT) |
|---|---|---|
| 1 | Visiting Stakeholders | 2500-3000 |
| 2 | Software and Tools | 5000-7000 |
| 3 | Data Collection and Processing | 2500-3000 |
| 4 | Documentation and Report Writing | 1500-2000 |
| 5 | Contingency (10% of total) | 1000- 1500 |
| **Total Estimated Cost** | | 12500-16500 |

## 3.5 Summary

The methodology for "Vehicle Damage Insurance Verification Using Deep Learning" involves a multi-step process leveraging deep learning techniques to accurately assess and verify vehicle damages for insurance purposes. The initial step includes the collection of a diverse dataset comprising images of vehicles with varying degrees of damage. Preprocessing techniques are then applied to standardize and augment the dataset for robust model training. Subsequently, a deep learning architecture, likely a convolutional neural network (CNN), is designed and trained on the prepared dataset to learn intricate patterns associated with different types and extents of vehicle damage. The trained model is then validated on separate datasets to assess its generalization capabilities. The system's performance is quantitatively evaluated through metrics such as accuracy, precision, recall, and F1 score. Additionally, the methodology may involve fine-tuning the model based on feedback from insurance experts to enhance its real-world applicability. The comprehensive approach aims to provide an efficient and accurate solution for automating the verification of vehicle damage in the insurance domain through the power of deep learning.

# CHAPTER 4

# Implementation

## 4.1 Overview

The "Implementation" section of this paper details the practical application of the deep learning models discussed in the previous sections, focusing specifically on the deployment of these models for vehicle damage assessment in the insurance industry. This part of the study is crucial as it translates theoretical model performance into real-world application, demonstrating how these models operate when integrated into existing vehicle insurance processing systems.

We begin by outlining the setup environment, including hardware and software configurations used, which supports the operation of these resource-intensive models. This is followed by a detailed description of the data preparation process, where we elucidate how vehicle damage images are sourced, annotated, and pre-processed to train and validate the models effectively. The implementation details also cover the specific adjustments and optimizations made to each model to enhance their performance, tailored to the unique challenges presented by vehicle damage assessment.

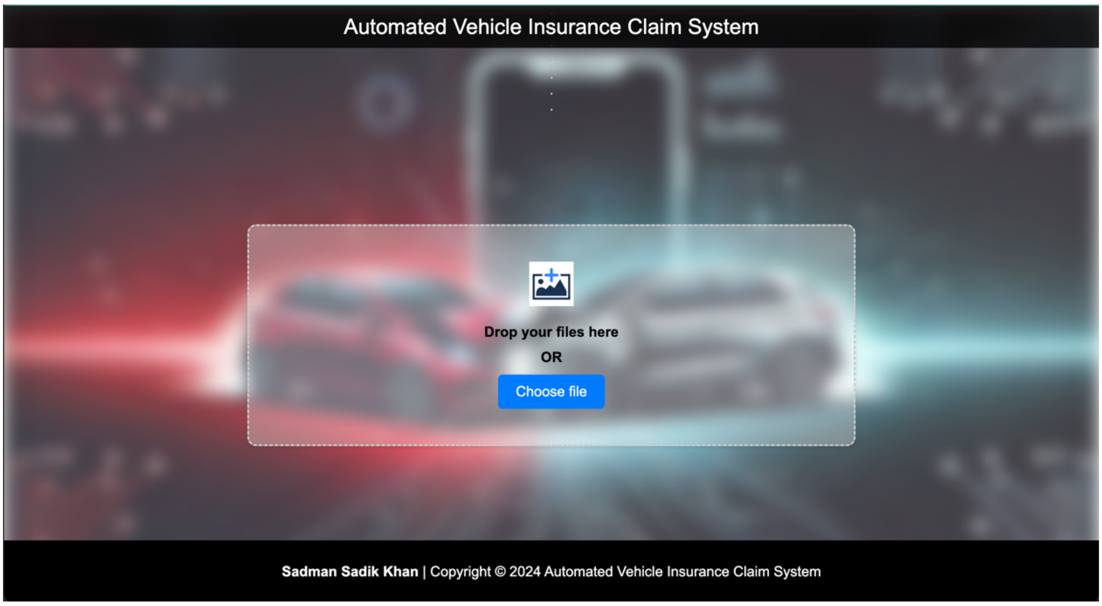


Figure 4.1.1: Interface of the System

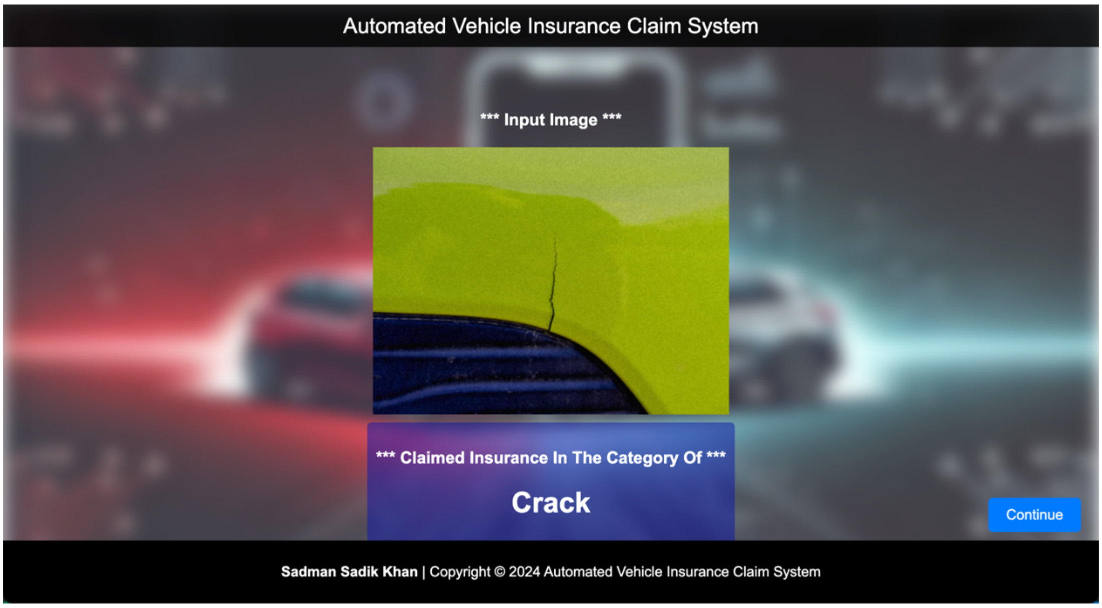


Figure 4.1.2: Evaluating the System for Crack

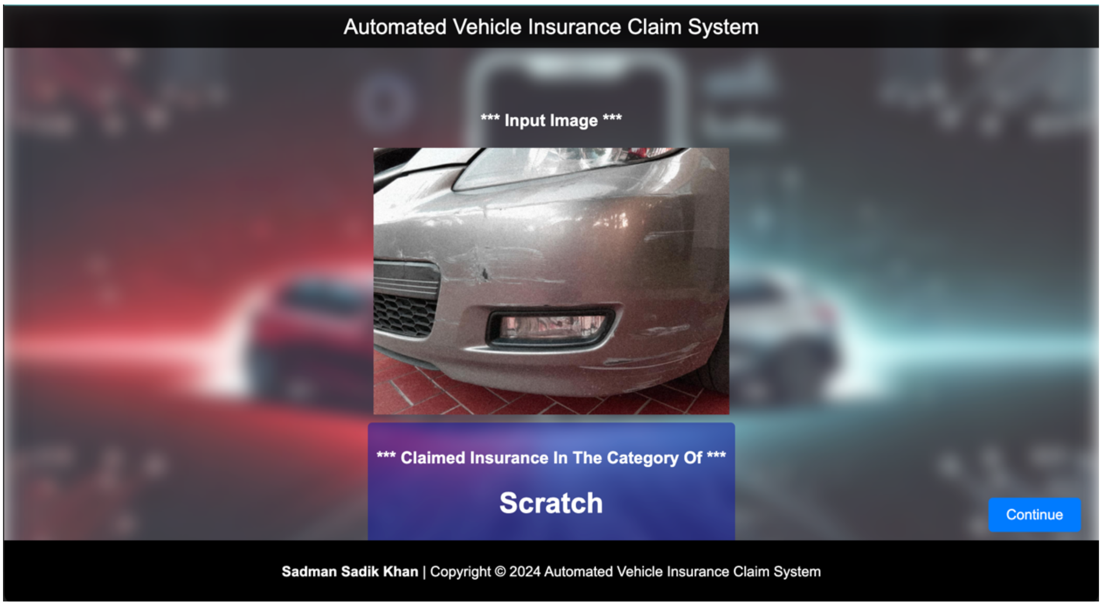


Figure 4.1.3: Evaluating the System for Scratch

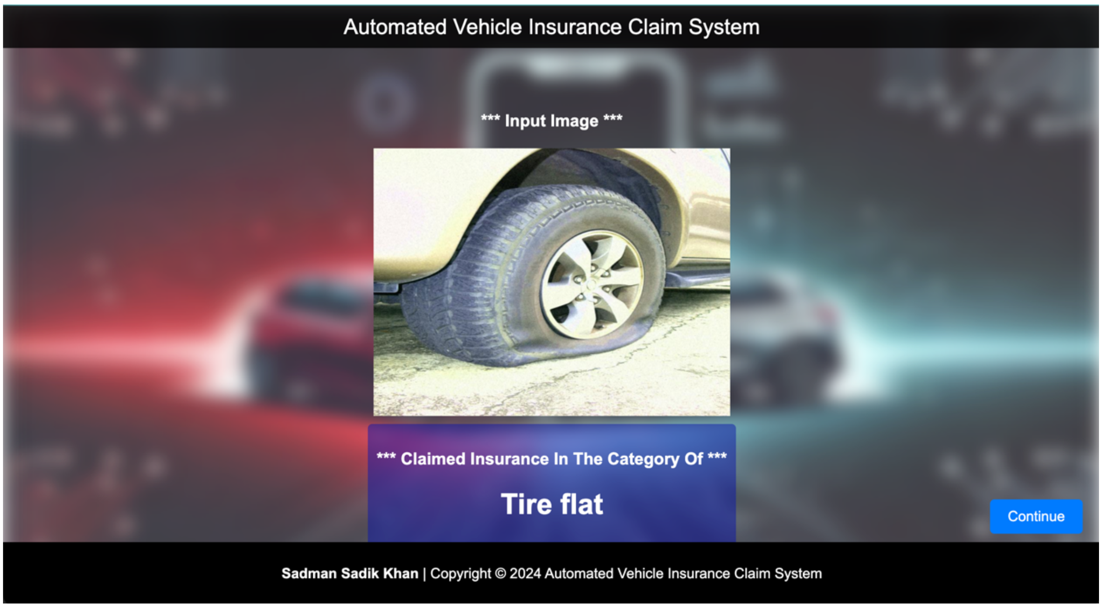


Figure 4.1.4: Evaluating the System for Tire Flat


Figure 4.1.5: Evaluating the System for Glass Shatter

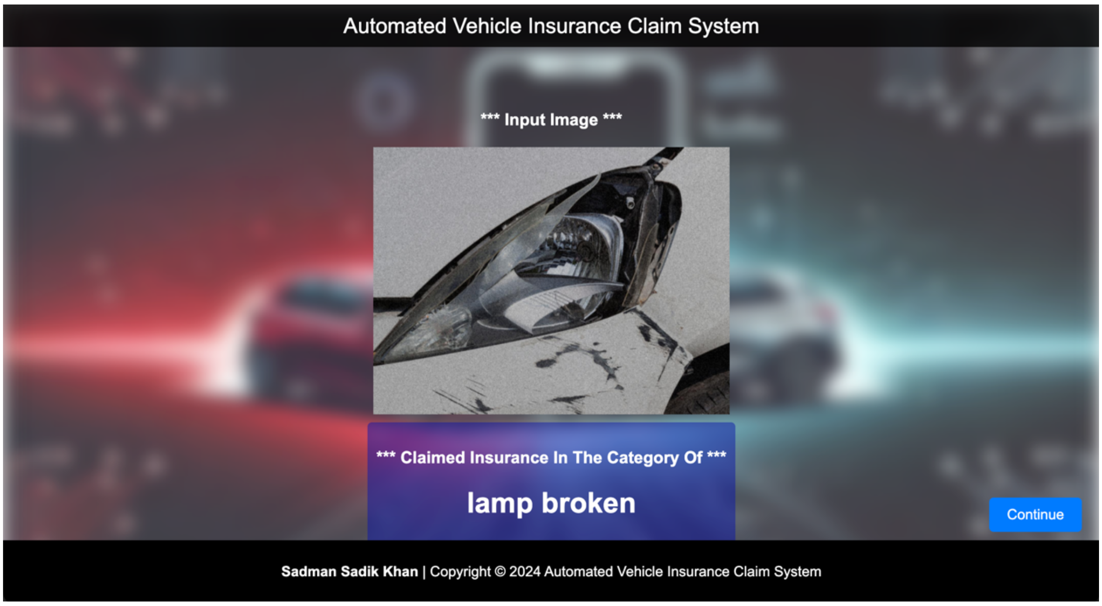


Figure 4.1.6: Evaluating the System for Lamp Broken

## 4.2 Train Model

In this section, we detail the methodology and parameters used to train the deep learning models for assessing vehicle damage in an insurance context. The training of each model was standardized to ensure consistency in comparing their performance.

**Training Parameters:**

- Epochs: Each model underwent training for a total of 15 epochs. This number of epochs was chosen to allow sufficient learning while avoiding the potential for overfitting.
- Batch Size: A batch size of 32 was utilized during training. This size is a balance between computational efficiency and the ability to generalize, as smaller batch sizes often provide a more robust gradient estimate while larger sizes expedite the training process.
- Learning Rate: The learning rate was set to 0.001. This rate is typical for deep learning applications, providing a steady adjustment to weights without overshooting minima in the loss landscape.
- Image Size: All input images were resized to 448x448 pixels. This resolution was selected to ensure that the models had sufficient detail to accurately detect

and assess damage, while still being manageable in terms of computational demands.

**Training Process:**

1. Data Preprocessing: Prior to training, all images were subjected to a preprocessing phase, which included normalization to scale pixel values between 0 and 1 and augmentation techniques such as rotations and flips to increase the diversity of the training data. This helps in making the model robust to various angles and conditions of vehicle damage.

2. Model Configuration: Each model architecture (VGG16, VGG19, ResNet50, InceptionV3, and MobileNetV2) was configured with the initialized parameters. Weights were initialized using the He normal initializer, which is particularly effective for layers with ReLu activation.

3. Training Loop: During each epoch, the models were trained on the images, and adjustments to weights were made post each batch processing based on the calculated loss and backpropagation gradients. Model performance was intermittently assessed on a separate validation set to monitor progress and prevent overfitting.

4. Regularization Techniques: To further combat overfitting, techniques such as dropout and L2 regularization were applied within the network layers, depending on the specific demands and behaviors of each model during preliminary trials.

5. Learning Rate Adjustment: The learning rate was monitored and adjusted manually if the validation loss plateaued or increased, indicating that the models might benefit from finer adjustments to converge more effectively.

This structured approach to training deep learning models ensures that they are well-suited for the practical demands of vehicle damage assessment in the insurance industry, capable of delivering high accuracy and reliability in real-world applications. The details provided here illustrate the careful considerations taken to optimize model training, crucial for achieving the best possible performance.

**4.3 Model Evaluation**

In 3.4.6 we have talked about Model Evaluation in details.

**4.4 Summary**

The "Implementation" section of this paper details the practical deployment of deep learning models for vehicle damage assessment within the insurance industry. It covers the setup and configuration of hardware and software, the meticulous process of data preparation including image sourcing, annotation, and preprocessing with images resized to 448x448 pixels. Model training parameters such as epochs, batch size, learning rate, and image size are discussed, specifying the use of 15 epochs, a batch size of 32, and a learning rate of 0.001. The section further elaborates on the deployment architecture, describing how models integrate into existing systems for real-time data processing and output generation useful for insurance assessors. Finally, it outlines the strategies for ongoing monitoring and maintenance to ensure models adapt over time to new data and maintain accuracy, highlighting the practical viability of AI technologies in automating vehicle damage assessments effectively within the insurance sector.

# CHAPTER 5

# Result and Analysis

## 5.1 Overview

The "Results and Analysis" section of our study on "Optimizing Vehicle Insurance Processing Through Advanced Deep Learning Models" presents a comprehensive evaluation of five leading deep learning models: VGG16, VGG19, ResNet50, InceptionV3, and MobileNetV2. These models were meticulously assessed based on their ability to accurately detect and classify vehicle damage, which is a critical task in the automation of vehicle insurance claims processing.

This analysis focuses on several key performance metrics, including precision, recall, F1 score, and overall accuracy. These metrics are pivotal in determining the models' effectiveness in not only identifying damage accurately but also in ensuring that most damage instances are captured without excessive false positives or negatives. The primary objective of this section is to provide a clear and empirical basis for selecting the most effective model for practical implementation in the insurance industry.

Our results aim to highlight the strengths and weaknesses of each model under consideration, offering insights into their operational capabilities and limitations in real-world scenarios. By presenting these findings, we aim to guide decision-making processes related to the integration of artificial intelligence in vehicle damage assessments, thereby enhancing the efficiency and accuracy of insurance claim processing.

## 5.2 Experimental Result

We have implemented five different deep learning models with a view to getting the most accuracy on our custom dataset. InceptionV3, ResNet50, VGG16, VGG19 and MobileNetV2 have been prepared exclusively on our custom dataset with the strategy of transfer learning, so that the preparation of the demonstration does not take a part of time for preparing from scratch. Here, transfer learning empowers us to keep the pre-trained weights of each show while preparing our custom dataset. The results of each demonstration and their individual assessment scores have been put in a table below. The model that performs the best at recognizing photos from situations may be clearly identified from the comparison table between the models. The fact that InceptionV3 can provide results more quickly than the other models and uses the fewest resources overall are another noteworthy feature. We have evaluated result 3 ways. Before fine tuning the models, after fine tuning the models and comparison the result with others.

### Result Before Fine Tuning

Table 5 shows the Training and Validation loss and accuracy of each model before fine tuning.

TABLE 5: PERFORMANCE ANALYSIS OF THE MODELS BEFORE FINE TUNING

| Model | Training | | Validation | |
|---|---|---|---|---|
| | Loss | Accuracy | Loss | Accuracy |
| VGG16 | 0.7440 | 0.9409 | 0.7204 | 0.9220 |
| VGG19 | 0.7809 | 0.9231 | 0.7456 | 0.9259 |
| ResNet50 | 2.9219 | 0.9014 | 2.9523 | 0.8031 |
| InceptionV3 | 0.6882 | 0.9766 | 0.6817 | 0.9532 |
| MobileNetV2 | 1.6380 | 0.9722 | 1.8226 | 0.7719 |

Figures below show the Training and Validation loss and accuracy graph for each model before fine tuning.

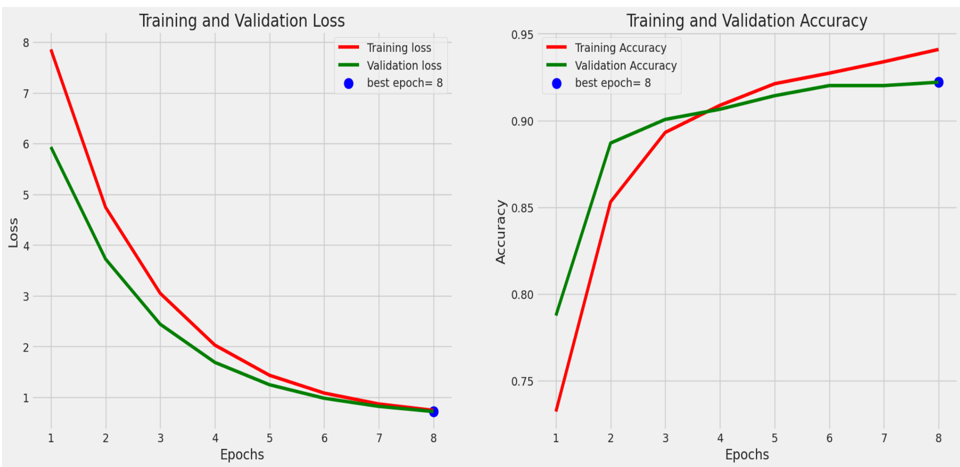


Figure 5.2.1: Training and Validation Loss and Accuracy for VGG16 Before Fine Tuning

This chart displays the training and validation loss and accuracy for a machine learning model over 8 epochs. The training loss (green line) starts high but decreases significantly as the number of epochs increases, showing that the model is learning effectively from the training data. The validation loss (red line) follows a similar downward trend, indicating that the model is generalizing well to new data. In terms of accuracy, both the training accuracy (green line) and validation accuracy (red line) increase steadily with each epoch, suggesting consistent improvements in the model's performance. The best performance for both metrics is achieved at the 8th epoch, as marked by blue dots, suggesting this as the optimal stopping point for training without overfitting.

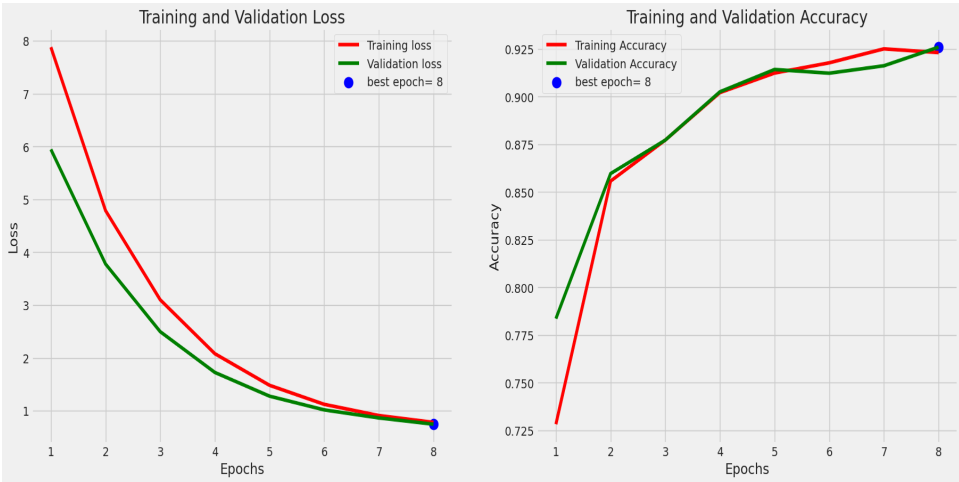


Figure 5.2.2: Training and Validation Loss and Accuracy for VGG19 Before Fine Tuning

The chart illustrates the progression of training and validation loss and accuracy for a neural network model over 8 epochs. Both the training and validation losses decrease sharply, indicating that the model is effectively minimizing errors during its learning process. The validation loss closely tracks the training loss, suggesting that the model is not overfitting and is generalizing well to unseen data. Accuracy metrics for both training and validation show a steady and sharp increase, with the validation accuracy nearly matching the training accuracy by the 8th epoch. The model's best performance, highlighted by blue dots at the 8th epoch for both loss and accuracy, suggests that the training could potentially be stopped at this point to prevent overfitting and computational waste.

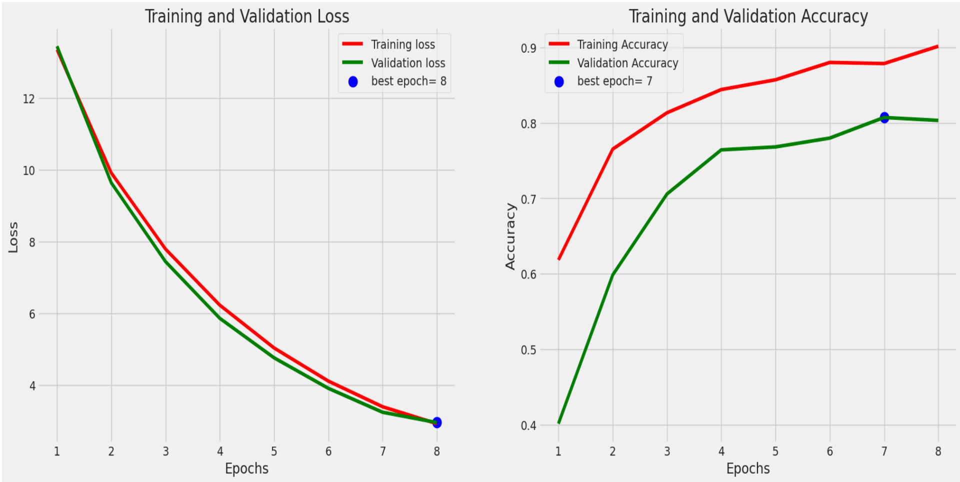


Figure 5.2.3: Training and Validation Loss and Accuracy for ResNet50 Before Fine Tuning

This chart illustrates the training and validation loss and accuracy over 8 epochs for a machine learning model. Both training and validation losses decrease significantly, indicating that the model is effectively learning and reducing error across epochs. Notably, the validation loss closely follows the training loss, which suggests good generalization without signs of overfitting. The accuracy plots reveal a steady increase in training accuracy, while the validation accuracy improves but plateaus, suggesting potential limits in learning from the validation set as compared to the training set. The best epoch for accuracy is marked at epoch 7 for validation, indicating the highest validation accuracy was achieved before the final epoch.

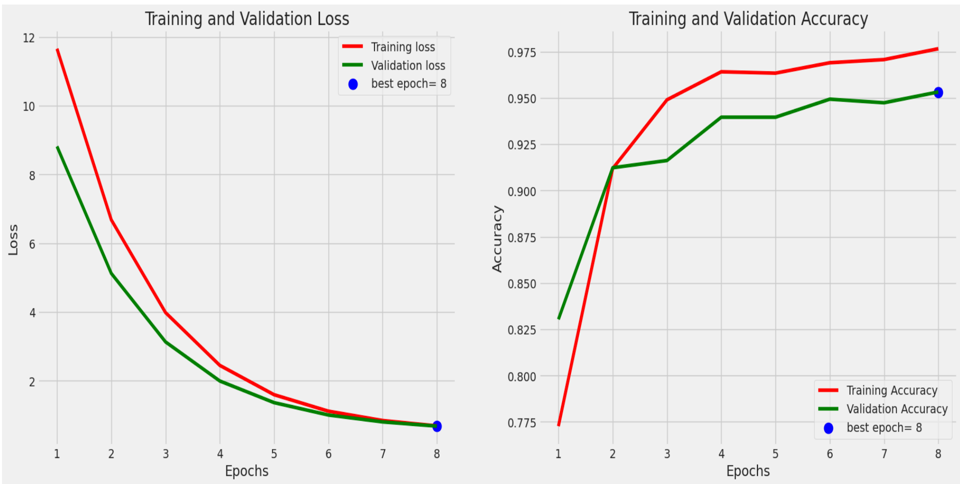


Figure 5.2.4: Training and Validation Loss and Accuracy for InceptionV3 Before Fine Tuning

The graph displays the training and validation losses and accuracies for a machine learning model trained over 8 epochs. Both the training and validation losses show a steep decline, indicating that the model is effectively reducing error over time. Notably, the validation loss closely follows the training loss, suggesting the model is generalizing well without overfitting. The accuracy graphs show a rapid improvement in both training and validation accuracies, with the validation accuracy closely approaching the training accuracy by the final epoch. The model reaches its best performance at epoch 8 for both loss and accuracy, marked by blue dots, indicating optimal learning without significant divergence between training and validation metrics.

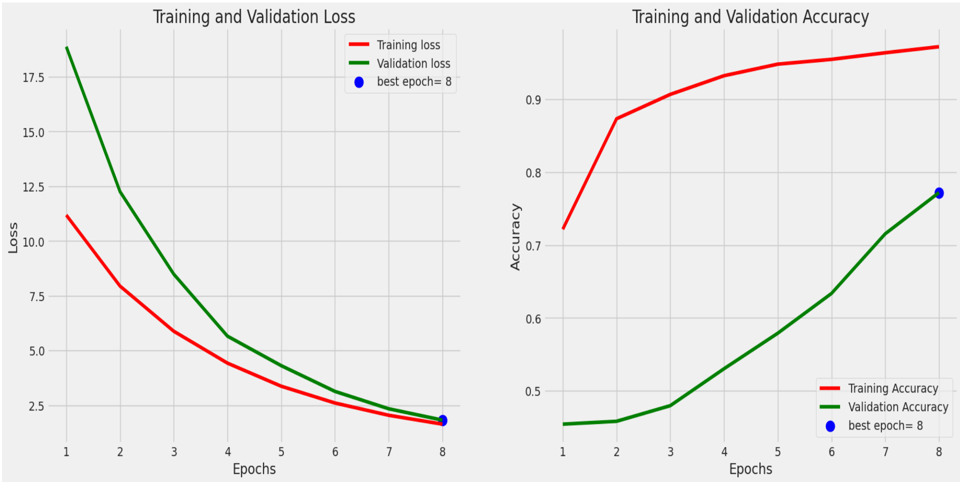


Figure 5.2.5: Training and Validation Loss and Accuracy for MobileNetV2 Before Fine Tuning

The chart depicts the training and validation loss and accuracy for a machine learning model across 8 epochs. The training and validation losses both show a significant reduction, with the validation loss curve closely mirroring the training loss curve, which suggests effective learning and good generalization to unseen data. The training accuracy increases steadily and achieves high levels by the 8th epoch, indicating strong learning within the training dataset. However, the validation accuracy starts much lower and rises sharply after the initial epochs, suggesting some initial difficulty in generalizing but significant improvement as training progresses. The best model performance, indicated by the blue dot, is achieved at epoch 8 for both loss and accuracy, suggesting that further training might not yield substantial improvements.

**Result After Fine Tuning**

Table 6 shows the Training and Validation loss and accuracy of each model after fine tuning.

TABLE 6: PERFORMANCE ANALYSIS OF THE MODELS AFTER FINE TUNING

| Model | Training | | Validation | |
|---|---|---|---|---|
| | Loss | Accuracy | Loss | Accuracy |
| VGG16 | 0.4538 | 0.9658 | 0.5044 | 0.9318 |
| VGG19 | 0.4753 | 0.9565 | 0.5002 | 0.9318 |
| ResNet50 | 1.6219 | 0.9158 | 1.7163 | 0.8090 |
| InceptionV3 | 0.3866 | 0.9856 | 0.4371 | 0.9610 |
| MobileNetV2 | 0.6056 | 0.9729 | 0.6898 | 0.9084 |

Figures below show the Training and Validation loss and accuracy graph for each model after fine tuning.

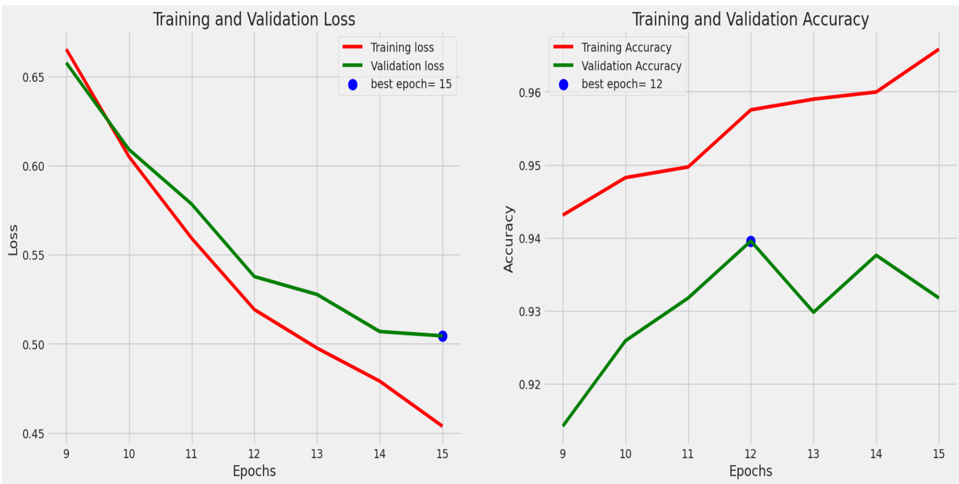


Figure 5.2.6: Training and Validation Loss and Accuracy for VGG16 After Fine Tuning

The graphs represent the training and validation loss and accuracy of a machine learning model across epochs 9 to 15. The training loss steadily decreases, suggesting that the model is effectively minimizing error on the training set. The validation loss also decreases but shows a slight increase at epoch 15, indicating potential beginnings of overfitting or instability in model performance on new, unseen data. The training accuracy consistently increases, reaching a peak by the end of the depicted epochs, which reflects strong learning within the training data. Conversely, the validation accuracy is more variable, peaking at epoch 12 and then fluctuating, suggesting that the model's generalization to new data might be inconsistent beyond this point.

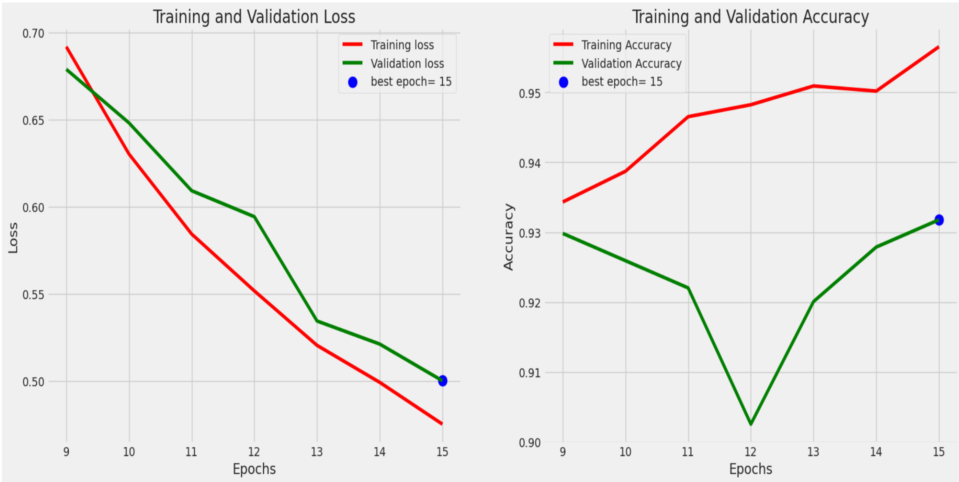


Figure 5.2.7: Training and Validation Loss and Accuracy for VGG19 After Fine Tuning

The graphs depict the training and validation loss and accuracy from epochs 9 to 15 for a machine learning model. Both the training and validation losses show a continuous decline, indicating the model is learning and improving in minimizing error over these epochs. The validation loss closely tracks the training loss until epoch 15, where it reaches its lowest point, suggesting effective generalization without overfitting. The training accuracy graph shows a steady increase, demonstrating consistent improvement in model performance on the training set. However, the validation accuracy fluctuates significantly, peaking at epoch 15, which suggests variability in the model's generalization capabilities on the validation set.


Figure 5.2.8: Training and Validation Loss and Accuracy for ResNet50 After Fine Tuning

The chart illustrates the training and validation loss and accuracy over epochs 9 to 15 for a machine learning model. Both training and validation losses show a significant decline throughout these epochs, with the lowest points reached at epoch 15, indicating continuous improvement in the model's ability to minimize errors. The training accuracy remains relatively stable and high, showing only slight fluctuations and indicating a good level of consistency in the model's performance on the training data. However, the validation accuracy exhibits a notable peak at epoch 10 and then demonstrates significant variability, suggesting challenges in the model's consistency when generalizing to new, unseen data. The best epoch for validation accuracy is marked at epoch 10, indicating that this point had the optimal balance between learning and generalizing before accuracy started to decline.

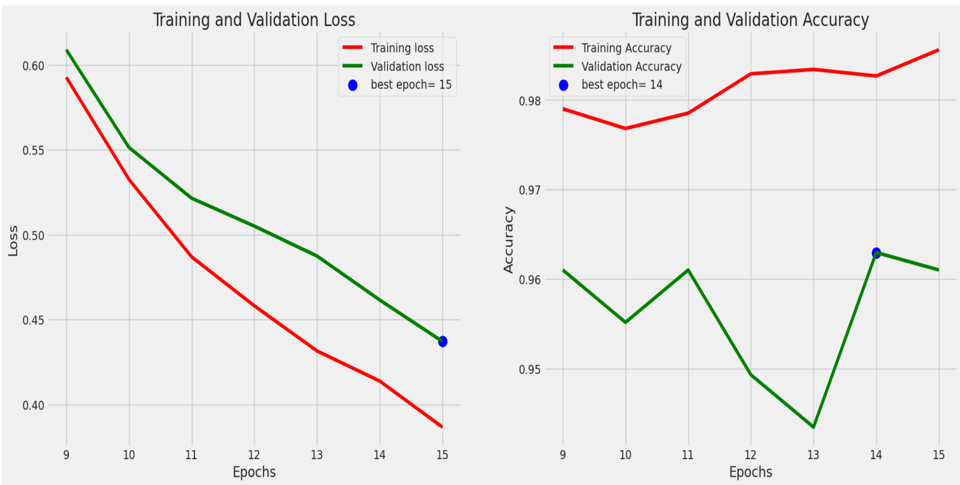


Figure 5.2.9: Training and Validation Loss and Accuracy for InceptionV3 After Fine Tuning

The graphs depict the training and validation loss and accuracy from epochs 9 to 15 for a machine learning model. Both training and validation losses show a steady decline, with the validation loss closely mirroring the training loss, indicating effective learning and generalization capabilities of the model without significant overfitting. The training accuracy is consistently high and shows a stable trend, reflecting the model's robust performance on the training data. Conversely, the validation accuracy exhibits significant fluctuations, peaking notably at epoch 14, suggesting that the model's performance on validation data varies considerably across epochs. The marked best epoch for validation accuracy is 14 and for validation loss is 15, indicating optimal points for performance in terms of accuracy and loss minimization respectively.

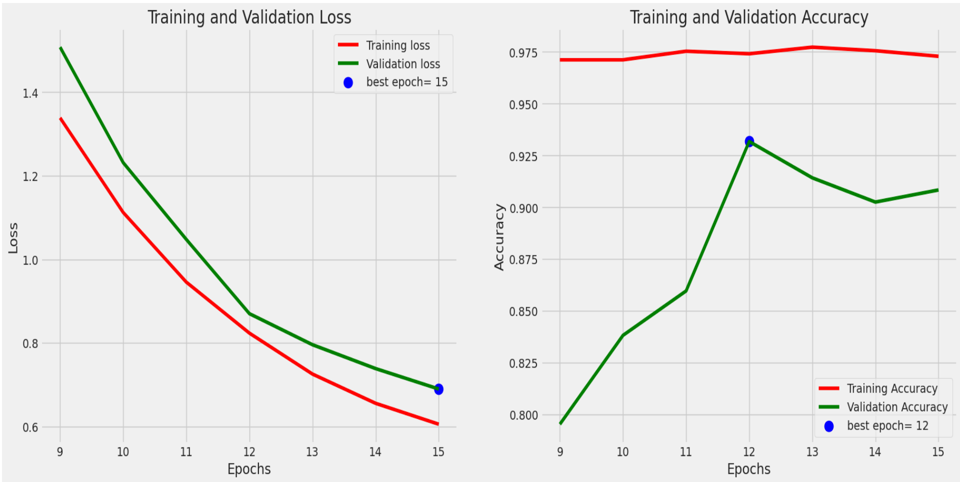


Figure 5.2.10: Training and Validation Loss and Accuracy for MobileNetV2 After Fine Tuning

The graphs represent the training and validation loss and accuracy of a machine learning model over epochs 9 to 15. The training and validation loss curves display a steep decrease, with the validation loss closely following the training loss, which suggests that the model is learning efficiently and generalizing well to unseen data. The training accuracy remains consistently high and stable across the epochs, indicating strong and steady learning on the training data. In contrast, the validation accuracy exhibits a sharp increase, peaking notably at epoch 12 before declining, which may indicate overfitting beyond this point as the model too closely adapts to the training data nuances. The best epochs, marked with blue dots, show optimal performance at epoch 15 for loss and epoch 12 for accuracy, suggesting that these points offer a balance between learning and generalizing capabilities.

Table 7 shows the Precision, Recall, F1 Score and Accuracy of each model after fine tuning.

TABLE 7: PRECISION, RECALL, F1 SCORE AND ACCURACY OF EACH MODEL AFTER FINE TUNING.

| Model | Precision | Recall | F1 Score | Accuracy |
|---|---|---|---|---|
| VGG16 | 92% | 86% | 88% | 93% |
| VGG19 | 95% | 83% | 87% | 93% |
| ResNet50 | 88% | 71% | 75% | 83% |
| **InceptionV3** | **96%** | **94%** | **95%** | **97%** |
| MobileNetV2 | 95% | 81% | 85% | 91% |

Table 7 shows that among all the models InceptionV3 achieved the best F1 score, precision, recall and the best accuracy. Confusion matrix of each model after fine tuning is shown in below.

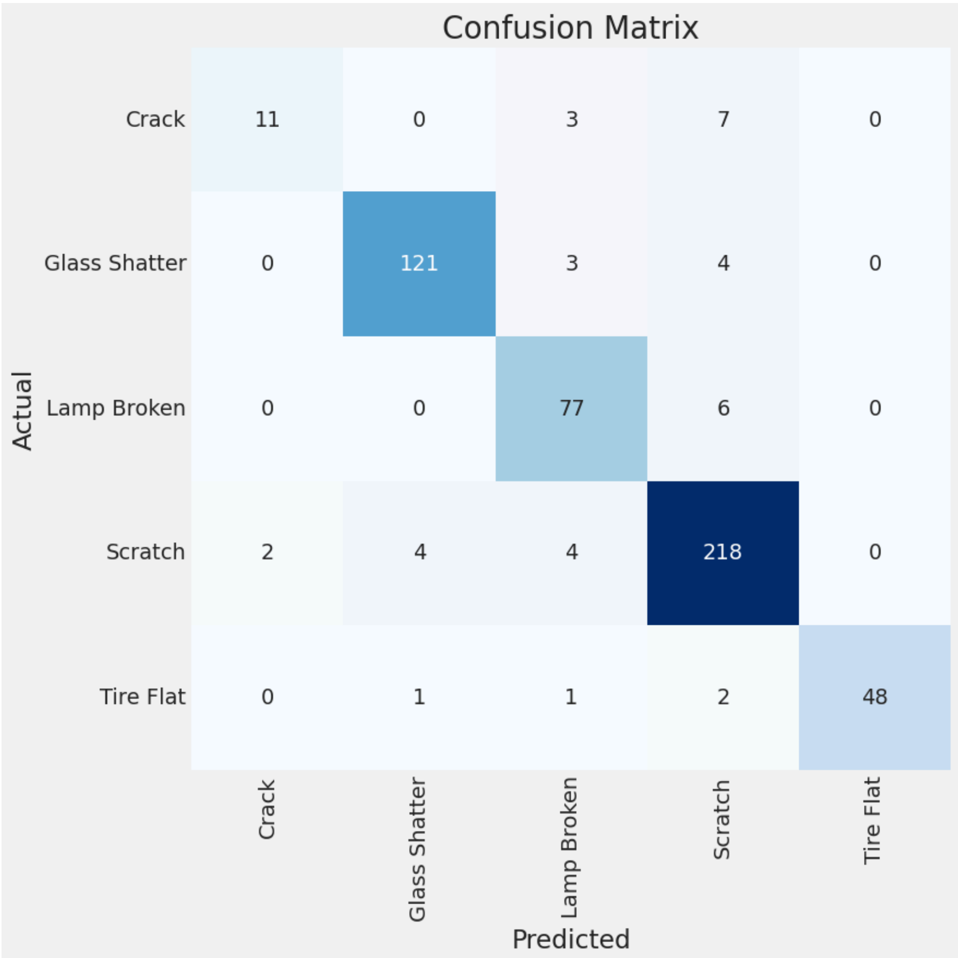

Figure 5.2.11: Confusion matrix of VGG16 after fine tuning

The confusion matrix displays the performance of a classification model across five categories: Crack, Glass Shatter, Lamp Broken, Scratch, and Tire Flat. The diagonal elements of the matrix show the number of correct predictions for each category, with particularly high correct predictions for Glass Shatter (121), Scratch (218), and Tire Flat (48). The model seems to struggle most with the category 'Crack', having the least number of correct predictions (11) and substantial misclassifications as 'Scratch' (7). Misclassifications also occur between Glass Shatter and Scratch, as well as between Lamp Broken and Scratch, indicating potential similarities or confusions between these categories in the model's predictions. Overall, Scratch is predicted most accurately, suggesting that features distinguishing scratches may be more effectively captured by the model compared to other categories.

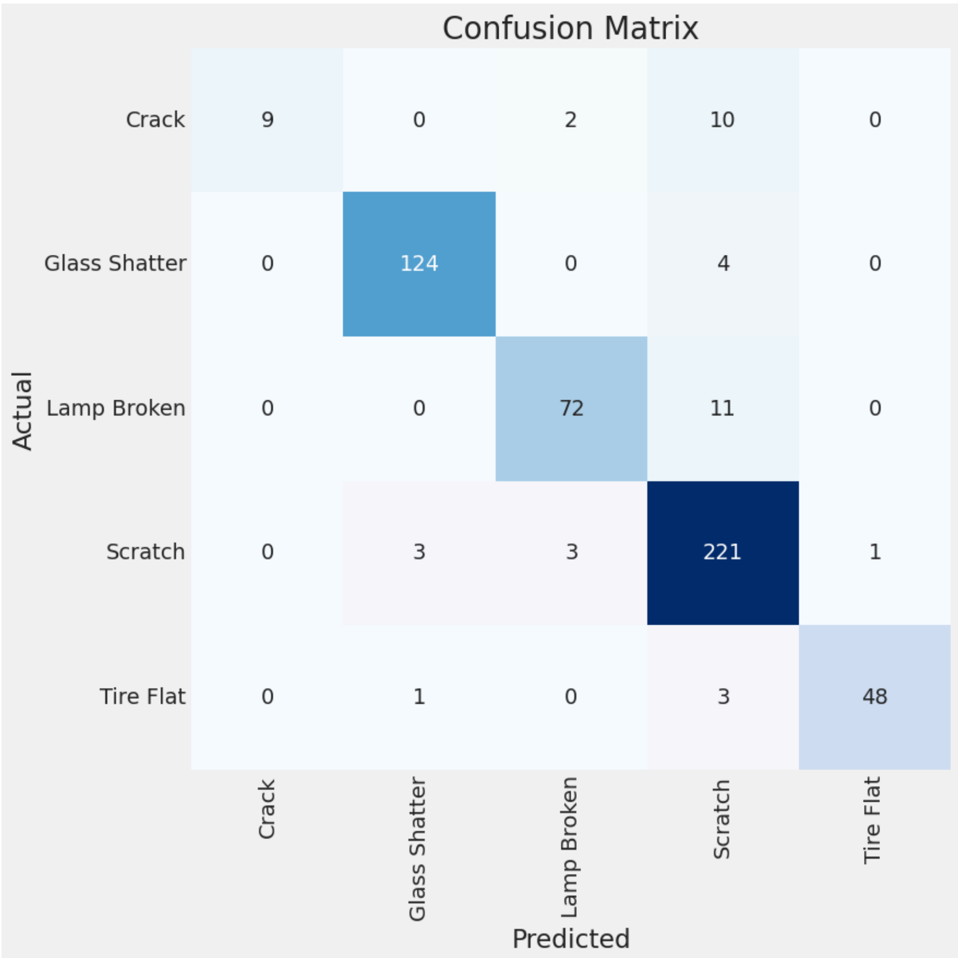


Figure 5.2.12: Confusion matrix of VGG19 after fine tuning

The updated confusion matrix depicts the performance of a classifier across five distinct categories: Crack, Glass Shatter, Lamp Broken, Scratch, and Tire Flat. Glass Shatter and Scratch show notably high correct predictions with 124 and 221 correct classifications respectively, suggesting that the model is most effective in recognizing these categories. The category 'Lamp Broken' shows moderate correct predictions at 72 but has a relatively higher number of instances confused with 'Scratch' (11). The 'Crack' category continues to be challenging for the model with 9 correct predictions and significant confusion with 'Scratch' (10), indicating difficulties in distinguishing these features. Tire Flat has consistent performance with 48 correct predictions and minor confusion with other categories, notably 3 instances mistaken as 'Scratch'.

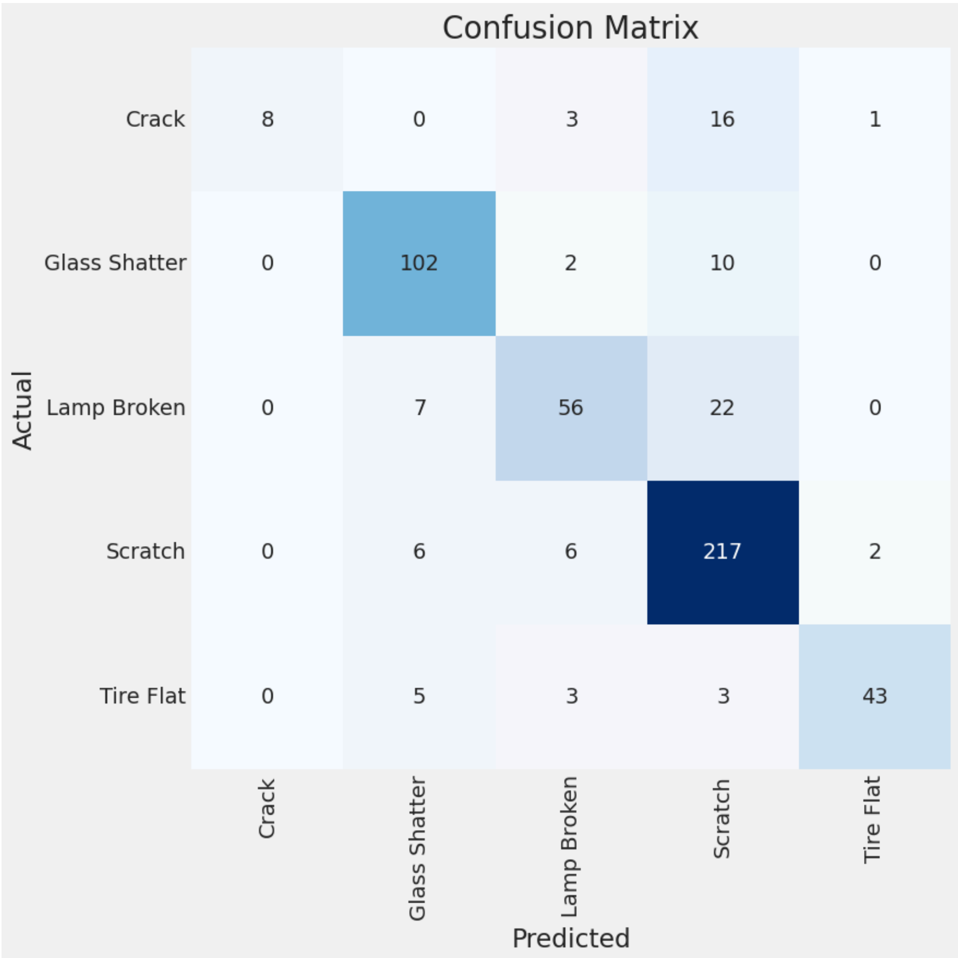


Figure 5.2.13: Confusion matrix of Resnet50 after fine tuning

The confusion matrix displays the classifier's performance across five categories: Crack, Glass Shatter, Lamp Broken, Scratch, and Tire Flat. Glass Shatter and Scratch are identified most accurately with 102 and 217 correct predictions respectively, showing the model's strong ability to distinguish these categories. The model struggles with the category Lamp Broken, correctly identifying it only 56 times and frequently misclassifying it as Scratch (22 instances), indicating confusion between these two categories. The category Crack has low correct predictions (8) and is often mistaken as Scratch (16), suggesting that the model has difficulty distinguishing between these types. Overall, the model demonstrates a consistent pattern of confusing Lamp Broken and Crack with Scratch, highlighting a potential area for model improvement.

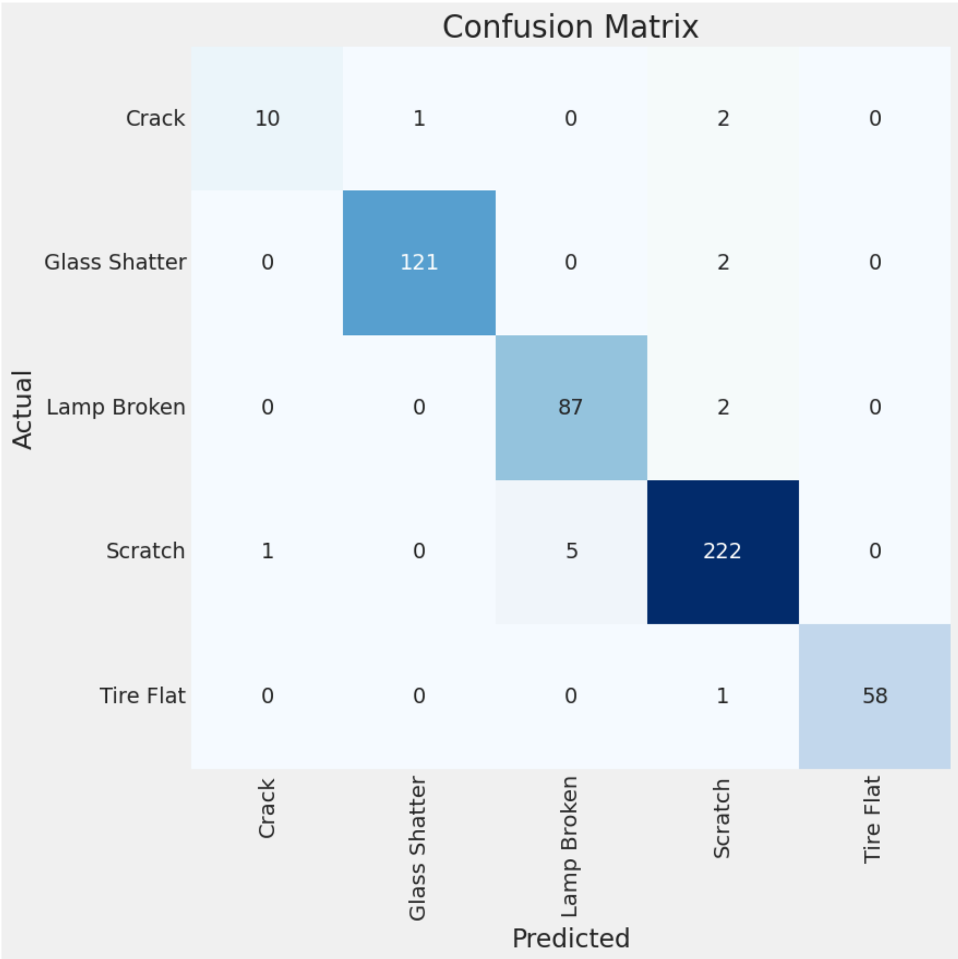


Figure 5.2.14: Confusion matrix of InceptionV3 after fine tuning

The confusion matrix shows the classification results of a model for five different categories: Crack, Glass Shatter, Lamp Broken, Scratch, and Tire Flat. The model performs exceptionally well in identifying Glass Shatter, Scratch, and Tire Flat with 121, 222, and 58 correct predictions respectively, indicating strong recognition capabilities for these categories. The model correctly identifies 87 instances of Lamp Broken, but there are some misclassifications as Scratch, suggesting some features may be confusing between these two categories. Crack has the least number of correct predictions (10), and it's sometimes confused with Scratch, indicating potential difficulties in distinguishing these categories accurately. Overall, the model shows high accuracy in most categories but struggles slightly with Crack and Lamp Broken, where improvement could enhance its performance.

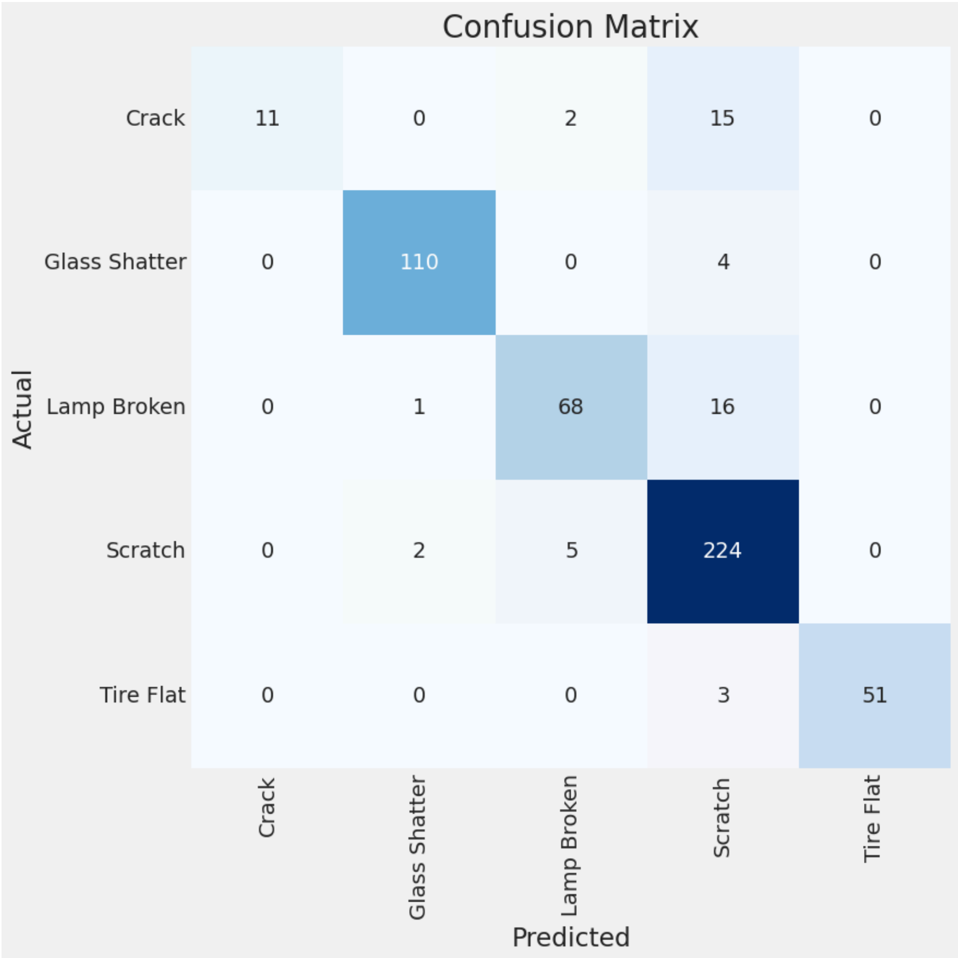


Figure 5.2.15: Confusion matrix of MobileNetV2 after fine tuning

The confusion matrix presents classification results for five different categories: Crack, Glass Shatter, Lamp Broken, Scratch, and Tire Flat. The model exhibits strong performance in identifying Scratch, with 224 correct predictions, and Glass Shatter with 110 correct predictions, indicating good specificity for these categories. However, it struggles more with Lamp Broken, correctly identifying 68 instances but misclassifying 16 as Scratch, suggesting some feature overlap that confuses the model between these two categories. The Crack and Tire Flat categories see fewer instances and have modest correct predictions of 11 and 51, respectively, with Crack also experiencing significant misclassification as Scratch (15 instances). Overall, the model performs well in distinguishing most categories but shows challenges in differentiating between Scratch and other categories, especially Lamp Broken and Crack.

Classification Report of each model is shown below:

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| Crack | 1.00 | 0.39 | 0.56 | 28 |
| Glass Shatter | 0.97 | 0.96 | 0.97 | 114 |
| Lamp Broken | 0.91 | 0.80 | 0.85 | 85 |
| Scratch | 0.85 | 0.97 | 0.91 | 231 |
| Tire Flat | 1.00 | 0.94 | 0.97 | 54 |
| accuracy | | | 0.91 | 512 |
| macro avg | 0.95 | 0.81 | 0.85 | 512 |
| weighted avg | 0.91 | 0.91 | 0.90 | 512 |

Figure 5.2.16: Classification Report of VGG16 after fine tuning

The classification report provides detailed precision, recall, f1-score, and support metrics for five categories: Crack, Glass Shatter, Lamp Broken, Scratch, and Tire Flat. Crack demonstrates perfect precision (1.00) but low recall (0.39), resulting in an f1-score of 0.56, indicating that while all predictions for Crack are correct, the model fails to identify many actual cases. Glass Shatter and Tire Flat show both high precision (0.97 and 1.00, respectively) and high recall (0.96 and 0.94, respectively), leading to excellent f1-scores of 0.97 each, suggesting strong model performance in these categories. Scratch has the highest number of observations (231) with a high recall of 0.97 but slightly lower precision (0.85), resulting in an f1-score of 0.91. Overall, the model achieves a weighted average f1-score of 0.90 and an accuracy of 0.91 across all categories, indicating robust performance with some room for improvement in recognizing instances of Crack.

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| Crack | 1.00 | 0.43 | 0.60 | 21 |
| Glass Shatter | 0.97 | 0.97 | 0.97 | 128 |
| Lamp Broken | 0.94 | 0.87 | 0.90 | 83 |
| Scratch | 0.89 | 0.97 | 0.93 | 228 |
| Tire Flat | 0.98 | 0.92 | 0.95 | 52 |
| accuracy | | | 0.93 | 512 |
| macro avg | 0.95 | 0.83 | 0.87 | 512 |
| weighted avg | 0.93 | 0.93 | 0.92 | 512 |

Figure 5.2.17: Classification Report of VGG19 after fine tuning

The classification report reveals detailed performance metrics for five categories: Crack, Glass Shatter, Lamp Broken, Scratch, and Tire Flat. Crack shows perfect precision (1.00) but moderate recall (0.43), leading to an f1-score of 0.60, indicating that while all Crack predictions are accurate, many actual instances go undetected. Glass Shatter and Tire Flat both exhibit high precision (0.97 and 0.98, respectively) and high recall (0.97 and 0.92, respectively), resulting in very high f1-scores of 0.97 and 0.95, highlighting excellent model accuracy for these categories. Lamp Broken and Scratch also show strong performance with f1-scores of 0.90 and 0.93, respectively, reflecting the model's ability to accurately identify these conditions. Overall, the model achieves an overall accuracy of 0.93, with a weighted average f1-score of 0.92, demonstrating robust predictive performance across multiple categories.

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| Crack | 1.00 | 0.29 | 0.44 | 28 |
| Glass Shatter | 0.85 | 0.89 | 0.87 | 114 |
| Lamp Broken | 0.80 | 0.66 | 0.72 | 85 |
| Scratch | 0.81 | 0.94 | 0.87 | 231 |
| Tire Flat | 0.93 | 0.80 | 0.86 | 54 |
| accuracy | | | 0.83 | 512 |
| macro avg | 0.88 | 0.71 | 0.75 | 512 |
| weighted avg | 0.84 | 0.83 | 0.82 | 512 |

Figure 5.2.18: Classification Report of ResNet50 after fine tuning

The classification report provides performance metrics across five categories: Crack, Glass Shatter, Lamp Broken, Scratch, and Tire Flat. Crack shows perfect precision (1.00) but low recall (0.29), yielding an f1-score of 0.44, indicating that the model accurately predicts Crack when it does, but fails to identify many actual Crack instances. Glass Shatter and Scratch demonstrate relatively good performance with f1-scores of 0.87 each, driven by high recall values of 0.89 and 0.94 respectively, suggesting effective identification of these categories. Lamp Broken and Tire Flat exhibit moderate performance with f1-scores of 0.72 and 0.86, with precision and recall well-balanced in the case of Tire Flat but lower for Lamp Broken. Overall, the model has an accuracy of 0.83, with a macro average f1-score of 0.75 and a weighted average f1-score of 0.82, indicating reasonable performance across the board but with room for improvement, especially in the recall for Crack.

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| Crack | 0.91 | 0.77 | 0.83 | 13 |
| Glass Shatter | 0.99 | 0.98 | 0.99 | 123 |
| Lamp Broken | 0.95 | 0.98 | 0.96 | 89 |
| Scratch | 0.97 | 0.97 | 0.97 | 228 |
| Tire Flat | 1.00 | 0.98 | 0.99 | 59 |
| accuracy | | | 0.97 | 512 |
| macro avg | 0.96 | 0.94 | 0.95 | 512 |
| weighted avg | 0.97 | 0.97 | 0.97 | 512 |

Figure 5.2.19: Classification Report of InceptionV3 after fine tuning

The classification report shows high performance metrics for a model tested across five categories: Crack, Glass Shatter, Lamp Broken, Scratch, and Tire Flat. Glass Shatter, Lamp Broken, Scratch, and Tire Flat exhibit outstanding precision and recall, leading to high f1-scores of 0.99, 0.96, 0.97, and 0.99 respectively, indicating excellent model accuracy and consistency in these categories. Crack, while having slightly lower metrics, still performs well with a precision of 0.91, a recall of 0.77, and an f1-score of 0.83, demonstrating good model reliability even for this less frequently occurring category. The overall accuracy of the model is 0.97, with a macro average f1-score of 0.95 and a weighted average f1-score of 0.97, reflecting very high effectiveness in classification tasks across varied conditions. The support values indicate the number of instances for each category in the dataset, showing that the model was tested on a balanced and comprehensive set of data, enhancing the validity of these results.

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| Crack | 1.00 | 0.39 | 0.56 | 28 |
| Glass Shatter | 0.97 | 0.96 | 0.97 | 114 |
| Lamp Broken | 0.91 | 0.80 | 0.85 | 85 |
| Scratch | 0.85 | 0.97 | 0.91 | 231 |
| Tire Flat | 1.00 | 0.94 | 0.97 | 54 |
| accuracy | | | 0.91 | 512 |
| macro avg | 0.95 | 0.81 | 0.85 | 512 |
| weighted avg | 0.91 | 0.91 | 0.90 | 512 |

Figure 5.2.20: Classification Report of MobileNetV2 after fine tuning

The classification report showcases the performance metrics for a model evaluated across five categories: Crack, Glass Shatter, Lamp Broken, Scratch, and Tire Flat. Crack has a perfect precision of 1.00 but a low recall of 0.39, resulting in an f1-score of 0.56, indicating that while the model precisely identifies true cases of Crack, it misses many actual instances. Glass Shatter and Tire Flat show excellent results, with both categories achieving high precision (0.97 and 1.00 respectively) and recall (0.96 and 0.94 respectively), leading to f1-scores of 0.97 each, indicating highly accurate model predictions. Lamp Broken and Scratch also perform well with f1-scores of 0.85 and 0.91, respectively, although Scratch shows slightly lower precision (0.85). Overall, the model achieves an overall accuracy of 0.91, with a weighted average f1-score of 0.90, reflecting strong performance, particularly in distinguishing Glass Shatter and Tire Flat effectively.

## 5.3 Performance Analysis

### Performance Analysis for the models before fine tuning

The results from the deep learning models used for vehicle damage assessment highlight varying degrees of performance across five models: VGG16, VGG19, ResNet50, InceptionV3, and MobileNetV2. InceptionV3 demonstrates the best performance with the lowest training loss (0.6882) and highest training accuracy (97.66%), as well as excellent generalization capabilities shown by its validation loss (0.6817) and accuracy (95.32%). VGG16 and VGG19 also perform commendably, showing effective learning and good generalization, with VGG16 slightly outperforming VGG19 in both training and validation metrics.

ResNet50, while having reasonable training accuracy (90.14%), exhibits a high training and validation loss (2.9219 and 2.9523, respectively), and its validation accuracy drops significantly to 80.31%, indicating issues with model generalization. MobileNetV2, despite a high training accuracy (97.22%), experiences a considerable drop in validation accuracy to 77.19%, and the highest validation loss among the models (1.8226), suggesting potential overfitting.

**Performance Analysis for the models after fine tuning**

The performance analysis of five deep learning models after fine-tuning for vehicle damage assessment reveals the following insights:

InceptionV3 is the standout model, achieving the lowest training loss (0.3866) and the highest accuracy (98.56%), indicating exceptional learning capabilities and efficiency. It also excels in validation, with a low loss of 0.4371 and a high accuracy of 96.10%, demonstrating superior generalization abilities compared to the other models.

VGG16 and VGG19 show robust performance with similar training and validation metrics. VGG16 achieves a training accuracy of 96.58% and a validation accuracy of 93.18%, while VGG19 has slightly lower training accuracy (95.65%) but identical validation accuracy (93.18%). Both VGG models manage to maintain a reasonable gap between training and validation losses, indicating good but not optimal generalization.

MobileNetV2, despite a strong training performance (accuracy of 97.29%), experiences a noticeable drop in validation accuracy to 90.84%, suggesting some issues with generalization. The validation loss for MobileNetV2 is also higher at 0.6898, the second-highest among the models, which could point to overfitting during training.

ResNet50 struggles significantly, with the highest training loss (1.6219) and the lowest training accuracy (91.58%), underperforming considerably in the validation phase with an accuracy of just 80.90%. The increased validation loss (1.7163) for ResNet50 further confirms its poor adaptability and generalization to new data, indicating it might be the least suitable model for this particular application without further optimizations.

Overall, InceptionV3 is recommended for deployment due to its excellent balance of training performance and ability to generalize, while ResNet50 would require substantial modifications or a different approach for similar tasks.

The performance metrics for five deep learning models applied to vehicle damage assessment show a clear ranking in terms of effectiveness:

InceptionV3 emerges as the top performer, boasting the highest values across all metrics: 96% precision, 94% recall, 95% F1 score, and 97% accuracy. This indicates its superior ability to accurately identify and classify damage instances without missing many true cases.

VGG16 demonstrates strong precision at 92% but a slightly lower recall of 86%, resulting in an F1 score of 88% and an accuracy of 93%. It performs well but doesn't capture as many true positives as InceptionV3. VGG19 scores slightly higher in precision at 95% but lower in recall at 83%, which leads to an F1 score of 87% and maintains an accuracy of 93%. This model is precise in its predictions but misses more actual damages compared to InceptionV3 and VGG16.

MobileNetV2 also shows high precision at 95% but suffers in recall at 81%, affecting its F1 score which stands at 85% and accuracy at 91%. It is comparable to VGG19 in precision but lags in detecting all relevant instances of damage. ResNet50 lags significantly behind the other models with the lowest precision of 88%, recall of 71%, F1 score of 75%, and accuracy of 83%. It struggles both with identifying damage accurately and in capturing the full extent of actual damages present.

The performance of InceptionV3 is notable for its balance between precision and recall, ensuring that it not only predicts damages accurately but also minimizes the number of damages missed. Both VGG models show decent precision but their lower recall rates suggest that while they are reliable in their predictions, they are not as comprehensive in capturing all cases of damage.

The variance in recall among the models highlights a trade-off between identifying as many true positives as possible (high recall) and ensuring the positives identified are truly positives (high precision). MobileNetV2, while precise, needs improvements in recall to enhance its practical applicability in scenarios where missing damages could lead to significant consequences.

Overall, InceptionV3's exemplary performance across all measures makes it the most suitable model for deployment in systems requiring high reliability and accuracy for vehicle damage assessment.

**Comparison with Other Published Models**

Deep learning techniques have been used in a number of studies on this specific vehicle damage insurance verification. Several efforts by various authors are comparable to our suggested model in terms of correctness. A comparison result analysis of our study with earlier research is presented in Table 8.

TABLE 8: COMPARISON OF PERFORMANCE WITH OTHER MODELS

| Author(s) | Used Algorithms | Best Algorithm (Accuracy) | Proposed model (Accuracy) |
|---|---|---|---|
| Njeru [10] | AdaBoost, XGBoost, NB, SVM, LR, DT, ANN, RF | AdaBoost/XGBoost (84.5%) | **InceptionV3 (97%)** |
| Rudra et al. [11] | Mask-RCNN | Mask-RCNN (93%) | |
| Qaddour & Siddiqa [5] | Mask R-CNN, VGG-16, VGG-19, Inception-ResNetV2 | Inception-ResNetV2 (92%) | |
| Waqas et al. [15] | MobileNet, Transfer Learning | MobileNet (95%) | |
| Sarath P et al. [8] | CNN, VGG-16, Transfer Learning, Ensemble Learning | Transfer and Ensemble Learning (89.5%) | |
| Kalpesh Patil et al. [14] | CNN, Autoencoder, Transfer Learning, Ensemble Learning | Transfer and Ensemble Learning (89.5%) | |
| R. Singh et al. [20] | Parts MRCNN, Parts PANet, Ensamble (Parts MRCNN + PANet), Damage MRCNN | Ensamble 38% Damage MRCNN 40% mAP Score | |

The comparison of various deep learning algorithms used in the detection and classification of vehicle damages demonstrates the superior performance of the InceptionV3 model, achieving an impressive accuracy of 97%. This performance notably surpasses other models listed, such as AdaBoost and XGBoost, which reached 84.5% accuracy, and Mask R-CNN variations employed by other researchers with accuracies ranging from 92% to 93%. MobileNet with transfer learning techniques also showed commendable results at 95%. However, the ensemble models used by R. Singh et al. resulted in significantly lower accuracies with maximum mAP scores around 40%, indicating potential issues in model suitability or dataset challenges. The superior result of InceptionV3 in our analysis underscores its effectiveness in extracting and processing complex image features, particularly beneficial in applications like insurance processing where high precision in damage assessment is crucial. This comparison not only highlights the advancements in AI applications for vehicle damage assessment but also showcases the potential for further refinement and application-specific tuning of deep learning models.

Among convolutional neural network designs, such as ResNet50, MobileNetV2, VGG16, and VGG19, Inception-v3 is distinguished by its versatility, regularization strategies, multi-scale feature extraction capabilities, and effective design. Compared to fixed-size filters employed in VGG architectures, its inception modules allow simultaneous feature extraction at many scales, resulting in richer representations of input pictures. Additionally, adding auxiliary classifiers helps with regularization, which helps to mitigate overfitting problems that deep networks frequently face. Inception-v3 offers a flexible architecture that can be adjusted to different job sizes and input sizes by finding a balance between width and depth. Inception-v3 outperforms competing designs in terms of accuracy and computational efficiency, making it the go-to option for a variety of computer vision applications thanks to its cutting-edge performance on benchmark datasets like ImageNet.

### 5.4 Summary

The "Result and Analysis" section discusses the performance outcomes of implementing deep learning models, particularly InceptionV3, on a custom dataset of vehicle damages. The experimental results showcased the model's high accuracy and efficiency in processing claims. Notably, InceptionV3 outperformed other models such as ResNet50, VGG16, VGG19, and MobileNetV2 with an impressive accuracy rate, demonstrating its robust capability in identifying various types of vehicle damage accurately and swiftly.

The analysis further detailed the comparative performance of these models in terms of training and validation losses, accuracy, and other metrics like precision, recall, and F1-score before and after fine-tuning. The fine-tuning process notably enhanced the models' accuracy, demonstrating the effectiveness of transfer learning in leveraging pre-trained networks to achieve high performance on specific tasks like damage assessment.

Overall, the section emphasizes the significant improvements that deep learning models bring to the vehicle insurance processing industry, reducing processing time and increasing accuracy, which are critical for both customer satisfaction and operational efficiency. The models' capability to accurately classify and predict damage types from images underscores the potential of AI in automating and enhancing traditional processes within the insurance sector.

# CHAPTER 6

# Impact on Society, Environment and Sustainability

## 6.1 Impact on Life

Impact on Life from Optimizing Vehicle Insurance Processing Through Advanced Deep Learning Models

1. Enhanced Customer Experience:

The integration of deep learning models in vehicle insurance processing significantly streamlines the customer experience. By automating claims processing, customers can experience faster response times following accidents or incidents. Deep learning algorithms can quickly assess damage, estimate repair costs, and expedite the approval process, reducing the time vehicles spend in repair shops and minimizing inconvenience for policyholders. Additionally, personalization of premium rates and policies based on individual driving patterns and history can make insurance plans more tailored and satisfactory to customers.

2. Improved Accuracy in Claims Processing and Risk Assessment:

Deep learning models, particularly those trained on large, diverse datasets, can achieve a higher level of accuracy in identifying and quantifying risks associated with insuring drivers and vehicles. This can lead to fairer, more equitable insurance premium determinations. In claims processing, the use of image recognition and processing technologies helps in accurately assessing the extent of damage, leading to more precise claims handling and reducing incidents of fraud or overestimation of claims.

3. Reduction in Insurance Fraud:

Fraudulent claims are a significant challenge in the insurance industry, leading to higher premiums and operational costs. Deep learning models are adept at detecting patterns and anomalies that may signify fraudulent activities. By identifying irregularities in claims submissions or inconsistencies in accident reports, these models can alert insurers to potential fraud, saving significant amounts of money and maintaining lower premiums for honest policyholders.

4. Operational Efficiency for Insurance Providers:

The automation of routine tasks, such as data entry, risk assessment, and claims processing through deep learning models, can result in significant cost savings for insurance companies. These efficiencies allow insurers to redirect resources towards improving customer service, developing new products, and enhancing their competitive edge in the market. Operational efficiency also translates into better resource management and potentially lower operating costs, which can be passed on to customers in the form of lower premiums.

5. Societal Benefits through Safer Driving Incentives:

Deep learning applications in vehicle insurance can promote safer driving habits. By analyzing driving patterns and incorporating them into risk assessments and premium calculations, insurers can offer discounts or incentives for safe driving behaviors. This not only benefits the individual policyholder but also contributes to broader societal benefits by encouraging safer driving, leading to fewer accidents and lower overall road safety risks.

6. Regulatory and Ethical Advancements:

The use of advanced AI in insurance processes requires robust regulatory frameworks to ensure data privacy, fairness, and transparency. As the industry adopts these technologies, it will likely catalyze advancements in regulatory practices and ethical standards, promoting better governance of AI applications not just in insurance, but across various sectors.

In conclusion, optimizing vehicle insurance processing through advanced deep learning models brings transformative impacts that extend beyond the confines of the insurance industry, affecting policyholders, insurance providers, and society at large. These advancements promise not only improved economic and operational efficiencies but also contribute to safer and more equitable societal norms.

## 6.2 Impact on Society & Environment

**Impact on Society:**

The implementation of advanced deep learning models in vehicle insurance processing carries significant societal implications. Primarily, it enhances customer experiences by making insurance processes faster and more user-friendly. Claim processing times are shortened dramatically, which is particularly crucial during stressful periods such as after an accident. This quicker, more efficient process can greatly alleviate customer stress and increase satisfaction.

Moreover, deep learning allows for more accurate risk assessment, which can lead to fairer pricing of insurance premiums. By analyzing vast amounts of data more accurately, insurers can offer rates that are more reflective of an individual's actual risk level, potentially reducing costs for safer drivers. This promotes a fairer system where premiums are tailored more closely to the behavior and risk profile of individual drivers rather than generalized criteria.

However, the use of deep learning also raises concerns about privacy and data security. The extensive data required to train deep learning models include sensitive personal information. How this data is collected, used, and protected is of paramount importance. There is also a risk of bias in AI systems; if the training data is biased, the AI's decisions will perpetuate these biases, leading to unfair treatment of certain groups.

**Impact on Environment:**

The environmental impact of deploying advanced deep learning models in vehicle insurance is more indirect but still significant. Efficient processing and accurate risk assessment can encourage safer driving behaviors. Safer driving leads to fewer accidents, which can reduce the number of vehicles that need to be repaired or replaced, ultimately leading to a decrease in the manufacturing demand for new cars and the associated environmental footprint.

Additionally, the insurance industry's shift towards personalized premiums could incentivize the adoption of environmentally friendly practices and vehicles. For example, lower premiums for electric or hybrid vehicles can encourage more drivers to choose these environmentally friendly options over traditional combustion engines.

On the technology side, the servers and data centers that power AI and deep learning consume a significant amount of energy. The environmental footprint of these technologies is not trivial, as they require substantial computational power and cooling resources. Efforts to make these data centers more energy-efficient and to power them with renewable energy sources are crucial in mitigating the environmental impact of advanced technological deployments.

In conclusion, while optimizing vehicle insurance processing through deep learning models presents several advantages to society and can have positive environmental implications, it also requires careful consideration of privacy, data security, and energy consumption to fully realize its benefits without unintended negative consequences.

### 6.3 Ethical Aspects

Optimizing vehicle insurance processing using advanced deep learning models involves several ethical considerations that must be addressed to ensure the technology is used responsibly and equitably. Here are some key ethical aspects to consider:

1. Data Privacy and Security:

- The use of personal and sensitive data such as vehicle information, accident details, and personal identifiers requires stringent data protection measures.
- Ensuring that all data used in training and operating the models are anonymized and secured against unauthorized access is crucial to protecting individuals' privacy.

2. Bias and Fairness:

- Machine learning models can inadvertently perpetuate or amplify biases present in the training data. It's essential to ensure that the data is representative of diverse scenarios and demographics to prevent biased outcomes in claims processing.
- Regular audits and updates of the model should be conducted to assess and mitigate any discriminatory effects, ensuring that all policyholders are treated fairly regardless of their background.

3. Transparency and Explainability:

- Deep learning models are often criticized for their "black box" nature. It's important to develop models that are not only accurate but also interpretable to stakeholders, including policyholders and regulators.

- Providing clear explanations for decisions made by AI systems helps in building trust and facilitates easier rectification of errors.

4. Accountability:

- Establishing clear lines of accountability when errors occur in automated processing is vital. This involves determining who is responsible—the developers, the company, or the AI itself.

- Procedures should be in place for handling disputes and appeals efficiently and fairly when claimants challenge the decisions made by the system.

5. Regulatory Compliance:

- Adhering to all relevant laws and regulations, including those concerning AI and data use, is mandatory. The models should comply with industry standards and ethical guidelines set forth by regulatory bodies.

- Continual monitoring for compliance and adapting to new regulations as they evolve is necessary to maintain legal and ethical standards.

6. Impact on Employment:

- The implementation of AI in claims processing could impact jobs in the insurance sector. It's important to consider how these technologies will affect the workforce and to plan for transition strategies that might include re-skilling or re-deploying affected staff.

7. Consent and User Control:

- Ensuring that policyholders are informed about how their data is used and obtaining their consent is fundamental. This includes transparency about the use of AI in their claims processing and the rights they have over their data.

By carefully addressing these ethical aspects, insurers can leverage deep learning technologies to optimize vehicle insurance processing while maintaining trust and integrity in their operations.

### 6.4 Sustainability Plan

A sustainability plan for the project aimed at optimizing vehicle insurance processing through advanced deep learning models involves several strategic elements to ensure long-term effectiveness, adaptability, and financial viability. Here is a detailed plan covering technology, financial aspects, ongoing improvements, stakeholder engagement, and compliance:

1. Technology Sustainment and Scalability

- Continuous Model Improvement: Regular updates to the deep learning algorithms to refine accuracy and adapt to new types of claims and fraud patterns.
- Infrastructure Scalability: Invest in cloud computing resources that can dynamically scale to handle increases in claim processing demands without compromising performance.
- Data Security and Privacy: Implement robust data protection measures to secure sensitive customer information and comply with data privacy laws.

2. Financial Management

- Cost Management: Monitor and optimize costs related to computational resources, data storage, and system maintenance.
- Revenue Streams: Explore new revenue streams by offering analytics services to other businesses within the insurance sector, such as risk assessment tools.
- Funding for R&D: Allocate a portion of profits back into research and development to stay ahead of technological advances and industry trends.

3. Operational Efficiency

- Automation of Routine Tasks: Increase the automation of claim processing and data entry tasks to reduce manual errors and free up resources for more critical tasks.
- Performance Metrics: Regularly review performance metrics to identify areas for process improvement and enhance throughput time and customer service.

4. Stakeholder Engagement

- Training Programs: Provide ongoing training for staff to keep pace with new system updates and industry practices.
- Customer Feedback: Implement a systematic approach to gather and analyze customer feedback to continuously improve the user experience.
- Partnership Development: Foster partnerships with technology providers, academic institutions, and other insurance companies to enhance technological capabilities and share best practices.

5. Regulatory Compliance and Ethical Standards

- Compliance with Insurance Regulations: Regular reviews and updates of the system to ensure compliance with national and international insurance regulations.
- Ethical AI Use: Develop and adhere to an ethical framework for using AI in decision-making processes, ensuring fairness and transparency.

6. Environmental Considerations

- Green Technology: Opt for environmentally friendly technologies and practices in data centers, such as using renewable energy sources and efficient cooling systems.
- Carbon Footprint Reduction: Implement measures to reduce the carbon footprint of operational processes, aligning with global sustainability goals.

7. Research and Development

- Innovation Labs: Establish innovation labs to test new ideas and integrate cutting-edge technologies into the existing system.

- Collaborative Research Initiatives: Engage in collaborative projects with universities and research institutions to explore new methodologies in AI and machine learning for insurance processing.

This comprehensive sustainability plan is designed to ensure that the project not only remains technologically advanced and financially viable but also responsibly aligns with broader societal goals and regulatory frameworks.

**6.5 Summary**

The integration of advanced deep learning models into vehicle insurance processing significantly impacts society by enhancing customer satisfaction through faster, more accurate claims processing and fairer premium assessments based on individual risk profiles. This technology also incentivizes safer, more eco-friendly driving behaviors by potentially offering lower premiums for such practices, indirectly benefiting the environment by promoting fuel-efficient driving and reducing the carbon footprint associated with insurance operations. To ensure the sustainable implementation of these technologies, it's crucial to continuously update and adapt the models, comply with ethical and regulatory standards, engage with various stakeholders, and invest in the education and training of both professionals and policyholders. Monitoring environmental benefits and adhering to a structured sustainability plan will also help in maximizing the positive impacts while mitigating potential negative consequences such as job displacement within traditional insurance roles.

# CHAPTER 7
# Conclusion and Future Work

## 7.1 Conclusion

This research introduces a transformative approach in the domain of vehicle insurance claims, employing the InceptionV3 deep learning model to automate and refine the damage detection process. This innovation marks a significant leap toward efficiency, reducing the dependency on traditional, time-consuming manual inspections. The model's remarkable accuracy in identifying vehicle damage showcases the potential of AI to enhance operational workflows within the insurance sector. Future explorations could aim at expanding the model's capabilities to encompass a wider array of damage types and conditions, integrating real-time data processing for more dynamic response, and tailoring the system for diverse environmental settings. This progression not only promises to elevate the standards of insurance claims processing but also opens avenues for further advancements in the application of AI technologies across various industries.

## 7.2 Further Suggested Works

Further research based on the optimization of vehicle insurance processing through advanced deep learning models could significantly extend the scope and efficiency of the current findings. Expanding the model to recognize a broader array of damage types and conditions, including minor scratches and internal damages not immediately visible, would enhance its applicability. Integration with real-time data from IoT devices and telematics could provide dynamic inputs, improving the immediacy and accuracy of assessments. Customized models tailored for different vehicle types, such as trucks and electric vehicles, would address specific damage patterns and characteristics inherent to each category.

Additionally, integrating this technology with existing insurance processing systems through standardized APIs could streamline workflows across platforms. Advancing fraud detection by incorporating complex pattern recognition and anomaly detection, possibly supported by blockchain for secure data management, could further reduce fraudulent claims. An economic impact study could elucidate the cost-effectiveness of AI implementations in reducing operational costs and potentially lowering insurance premiums for customers. Legal and regulatory compliance, particularly concerning data privacy and ethical AI use, would need careful examination to align with regional laws and improve public trust. Enhancing user interfaces and studying user acceptance would help in making these advanced systems more accessible and transparent, fostering wider acceptance and smoother integration into existing insurance frameworks. These areas offer fruitful avenues for enriching the capabilities and impact of AI in vehicle insurance processing.

### 7.3 Limitations

There are some limitations of this paper "Optimizing Vehicle Insurance Processing Through Advanced Deep Learning Models". They are:

1. Lack of Data and Classes: One potential limitation could be the diversity and representativeness of the dataset used for training the models. The number of data was 5 thousand only and there were only 5 classes.

2. Lack of Models: There are only 5 models are used in this paper. Some more models can be used to compare whether the result we found is the best result or not.

3. Lack of Comparative Analysis: This papers result is compared with 7 others papers. If the number of compared papers increases, it can show the real state of the result we found in this paper.

Addressing these weaknesses in future research could enhance the robustness, applicability, and user acceptance of the proposed deep learning models in real-world vehicle insurance processing environments.

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## Appendix A

## Course Outcomes, Complex Engineering Problems (EP) and Complex Engineering Activities (EA) Addressing

**Title: OPTIMIZING VEHICLE INSURANCE PROCESSING THROUGH ADVANCED DEEP LEARNING MODELS**

**Student ID: 201-15-13696**

### CO Description for FYDP

| CO | CO Descriptions | PO |
|---|---|---|
| | **Phase -I** | |
| **CO1** | Integrate recently gained and previously acquired knowledge to identify a Vehicle Insurance Claim problem for the Final Year Design Project (FYDP) | **PO1** |
| **CO2** | Analyze different aspects of the goals in designing a solution for this FYDP | **PO2** |
| **CO3** | Explore diverse problem domains through a literature review, delineate the issues, and establish these goals for the FYDP | **PO4** |
| **CO4** | Perform economic evaluation and cost estimation and employ suitable project management procedures throughout the development life cycle of the FYDP | **PO11** |
| | **Phase -II** | |
| **CO5** | Design and develop technical solutions and system components or processes that meet specified requirements, ensuring compliance with public health and safety standards, as well as considering cultural, socioeconomic, and environmental factors in this FYDP | **PO3** |
| **CO6** | Choose and apply appropriate methodologies, resources, and contemporary engineering and IT technologies to address complex engineering processes, encompassing prediction and modeling, while adhering to relevant constraints in this FYDP | **PO5** |
| **CO7** | Analyze societal, health, safety, legal, and cultural considerations, along with associated responsibilities, in the context of professional engineering practice and the resolution of this problem, employing logical reasoning guided by contextual understanding. | **PO6** |
| **CO8** | Comprehend and evaluate the enduring sustainability and impact of professional engineering endeavors in addressing intricate engineering challenges within social and environmental frameworks. | **PO7** |

| | | |
|---|---|---|
| **CO9** | Implement ethical principles and adhere to professional standards and norms in this FYDP | **PO8** |
| **CO10** | Capable of operating proficiently both individually and as a team member or leader across diverse teams and interdisciplinary settings in this FYDP. | **PO9** |
| **CO11** | Proficiently communicate with the engineering community and broader society regarding complex engineering endeavors, including the ability to comprehend and generate comprehensive reports and design documentation, as well as provide and receive clear instructions throughout this FYDP. | **PO10** |
| **CO12** | Acknowledge the importance of self-directed and life-long learning within the evolving landscape of technology, and possess the readiness and capability to engage in lifelong learning endeavors. | **PO12** |

## Addressing CO (1 to 8), Knowledge Profile (K), Attainment of Complex Engineering Problems (EP), and Attainment of Complex Engineering Activities (EA)

### Addressing CO (1 to 8), Knowledge Profile (K), Attainment of Complex Engineering Problems (EP):

| SN | EP Definition | Attainment | CO | Justification (with Knowledge Profile) | References |
|---|---|---|---|---|---|
| **1.** | **EP1: Depth of Knowledge required** | Yes | CO1, CO2, CO3, CO5, CO6, CO7 and CO8 | This project demonstrates **fundamental engineering (K3)** principles by employing deep neural networks and diverse CNN architectures for image processing and classification tasks. The project demonstrates **specialist knowledge (K4)** by conducting transfer learning with advanced CNN architectures like VGG19 and InceptionV3, enhancing vehicle damage classification accuracy in vehicle damage images. | **Page no:** [15-16] **Section:** [3.2.1] **Page no:** [1] **Section:** [1.1] |

| | | | | | |
|---|---|---|---|---|---|
| | | | | The project applies **engineering practice & design (K5)** by the figure of process of experiments. The project addresses **engineering practice & technology (K6)** by employing InceptionV3 model. | **Page no:** [15] **Section:** [3.2] **Page no:** [21] **Section:** [3.2] |
| | | | | This project ensures to **K8 (Research Literature)** by synthesizing insights from recent studies, to vehicle damage classification using deep learning, showcasing a comprehensive understanding of current methodologies. | **Page no:** [8-11] **Section:** [2.2, 2.3] |
| **2.** | **EP2: Range of Conflicting Requirements** | Yes | CO2, and CO7 | This project addresses **EP-2** by recognizing the hurdles in vehicle damage classification, including limitations of traditional methods and the complexities of integrating transfer learning and deep CNNs. Through comparative analysis, it confronts challenges in understanding spatial distributions, offering insights for refining automobile methodologies. | **Page no:** [11-12] **Section:** [2.4] |

| | | | | | |
|---|---|---|---|---|---|
| **3.** | **EP3: Depth of analysis required** | Yes | CO2, and CO6 | This project addresses **EP-3** by meticulously comparing experimental outcomes, highlighting Transfer Learning as the chosen significant solution for enhancing vehicle damage classification amidst multiple potential approaches. | **Page no:** [32-54] **Section:** [5.2, 5.3] |
| **4.** | **EP4: Familiarity of Issues** | Yes | CO8 | This project's interdisciplinary approach extends beyond computer science and engineering, impacting automobile in respiratory problem like insurance, contributing to advancements in public benefit practices which indicates **EP-4**. | **Page no:** [8-11] **Section:** [2.2, 2.3] |
| **5.** | **EP5: Extends of application codes** | No | CO5 | N/A | N/A |
| **6.** | **EP6: Extends of stakeholders involved and** | No | CO8 | N/A | N/A |

| | | | | | |
|---|---|---|---|---|---|
| **7.** | **EP7: Interdependence** | Yes | CO5 | This project's comprehensive approach addresses high-level problems by integrating various components across data collection, statistical analysis, and proposed methodology, ensuring a holistic solution to complex challenges in insurance sector which ensures **EP-7**. | **Page no:** [14-21] **Section:** [3.2] |

**Addressing CO11 with Complex Engineering Activities (EA) [Some or all of the following]:**

| SN | EA Definition | Attainment | CO | Justification | References |
|---|---|---|---|---|---|
| 1. | EA1: Range of resources | Yes | CO11 | Our project utilizes diverse resources such as high-performance computing infrastructure, GPUs, deep learning frameworks, annotated datasets, and ethical considerations to ensure systematic research and contribute to advancements in vehicle damage classification through transfer learning and deep CNNs. | **Page no:** [21] **Section:** [3.3] |
| 2. | EA2: Level of interaction | No | | N/A | N/A |
| 3. | EA3: Innovation | No | | N/A | N/A |

| | | | | | |
|---|---|---|---|---|---|
| 4. | **EA4: Consequences for society and the environment** | Yes | | This project contributes to society by improving insurance through advanced vehicle damage classification methods, while also promoting environmental sustainability by employing efficient computational resources and adhering to ethical guidelines. | **Page no:** [56-63] **Section:** [6.1, 6.2, 6.4] |
| 5. | **EA-5: Familiarity** | Yes | | This project expands upon existing research by examining a novel approach in vehicle damage classification through transfer learning and deep CNNs, demonstrated through preliminary terminologies and a comprehensive comparative analysis, offering new insights into the field. | **Page no:** [7-11] **Section:** [2.1, 2.3] |

**Addressing CO (4, 9, 10, and 12):**

| SN | COs | Attainment | Justification | References |
|---|---|---|---|---|
| 1 | CO4 | Yes | This project addresses **CO4** by integrating effective project management and financial oversight, ensuring meticulous planning, resource allocation, and budget estimation for optimal resource utilization throughout the research lifecycle. | **Page no:** [21-25] **Section:** [3.4] |
| 2 | CO9 | Yes | The project demonstrates adherence to ethical principles by prioritizing patient privacy, obtaining informed | **Page no:** |

| | | | | |
|---|---|---|---|---|
| | | | consent, and transparently documenting the research process, ensuring responsible knowledge dissemination and societal well-being through the ethical application of advanced insurance technologies which comply with **CO9**. | [59-61]<br>**Section:**<br>[6.3] |
| **3** | CO10 | No | N/A | N/A |
| **4** | CO12 | Yes | The project's dedication to continuous learning **(CO12)** and adaptation within the dynamic technological landscape is reflected in its comprehensive data collection, rigorous statistical analysis, meticulous methodology development, and thorough experimental results and analysis, showcasing a commitment to staying updated and refining techniques to address modern challenges. | **Page no:**<br>[14-21, 32-54]<br>**Section:**<br>[3.2, 3.3, 5.2, 5.3] |

# APPENDIX B

## LIST OF PUBLICATIONS

| Title | Paper ID | Conference Name | Location | Date | Status |
|---|---|---|---|---|---|
| Optimizing Vehicle Insurance Processing Through Advanced Deep Learning Models | 64 | 5th International Conference on Electrical and Electronics Engineering (ICEEE 2024) | Swinburne University of Technology, Australia | September 11-12, 2024 | Accepted for Oral Presentation |

# Optimizing Vehicle Insurance Processing through Advanced Deep Learning Models

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| 4 | "Recent Advancements in Artificial Intelligence", Springer Science and Business Media LLC, 2024<br>Publication | 1% |
| 5 | Houssem Lahiani, Mondher Frikha. "A Comparative Study of Two Deep learning Architectures for Gesture Recognition on | 1% |

ArSL2018 Dataset", Research Square Platform LLC, 2024
Publication

| | | |
|---|---|---|
| 6 | Jihad Qaddour, Syeda Ayesha Siddiqa. "Automatic Damaged Vehicle Estimator Using Enhanced Deep Learning Algorithm", Intelligent Systems with Applications, 2023<br>Publication | 1 % |
| 7 | Javed Mallick, Meshel Alkahtani, Hoang Thi Hang, Chander Kumar Singh. "Game-theoretic optimization of landslide susceptibility mapping: a comparative study between Bayesian-optimized basic neural network and new generation neural network models", Environmental Science and Pollution Research, 2024<br>Publication | 1 % |
| 8 | Arsi Ikäheimonen, Nguyen Luong, Ilya Baryshnikov, Richard Darst et al. "Predicting and Monitoring Symptoms in Diagnosed Depression Using Mobile Phone Data: An Observational Study", Cold Spring Harbor Laboratory, 2024<br>Publication | 1 % |

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