Optimizing Vehicle Insurance Processing through Advanced Deep Learning Models

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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.**

Keywords*— *Vehicle damage detection, Deep learning, InceptionV3, Architecture of InceptionV3, AI based insurance system

I. INTRODUCTION

The incidence of vehicle accidents in Bangladesh has significantly increased in recent years [1]. Based on NISCHA's statistics during the preceding eight years, there were a total of 2,626 mishaps in the year 2015. In the year 2016, a total of 2,316 accidents occurred. In 2017, there were 3,349 accidents that resulted in the loss of 5,645 lives. In 2018, the number of mishaps increased to 3,103, resulting in the loss of 4,839 lives. In 2019, there was a significant increase with a total of 4,702 incidents resulting in 5,227 fatalities and 6,953 injuries. In 2020, there was a little decrease, with a total of 4,092 mishaps. In 2021, there were 4,983 accidents that resulted in 5,689 fatalities and 5,805 injuries. In 2022, there was a significant increase in the number of incidents, reaching a total of 7,024. These incidents resulted in 8,104 fatalities and caused injuries to 9,783 individuals [2].

According to Save the Road's figures, there were 10,261 mishaps in 2015. In 2016, the number of mishaps increased to 12,607. In 2017, there were a total of 13,959 accidents, resulting in 4,664 deaths and 13,593 injuries. In the year 2018, a total of 13,621 mishaps occurred. The number of accidents in 2019 decreased to 11,751, resulting in 3,938 fatalities and 9,399 injuries. In the year 2020, there were a total of 8,690 documented events. There were a total of 7,512 mishaps in the year 2021. The statistics for 2022 were remarkable, with a total of 52,048 incidents, resulting in 9,434 fatalities and 45,337 injuries [2].

According to the regulations stated in the Motor Vehicles Ordinance, 1983 (referred to as the MVO, 1983), it was compulsory for motor vehicle owners to have insurance, except for government-owned vehicles. The recently implemented Road Transport Act of 2018 has granted owners the choice to obtain an insurance policy [4].

While insurance is currently not obligatory in Bangladesh, many individuals opt to obtain an insurance coverage to ensure they can make a claim in the event of any unexpected occurrences. However, the insurance claims process is excessively protracted. Initially, insurance firms do a thorough examination of the incident area, vehicle, and relevant paperwork. The process of claiming insurance can be prolonged, causing significant distress for individuals over a span of several weeks. Given the many situations, the optimal way to decrease human responsibility in this matter could be an AI-based system, which has been demonstrated to have a significant impact. This difficulty can be readily solved using a computer vision-based program. In order to address the need, it is imperative to develop an insurance verification system utilizing machine learning algorithms. This system would enable us to place trust in the computer's decision-making capabilities, thereby circumventing the limitations associated with depending just on human observations.

In the contemporary era, all challenges can be resolved using artificial intelligence (AI) technology. For a considerable duration, countries in the modern world have been endeavoring to develop an automated insurance system. In recent decades, there have been numerous research endeavors focused on developing algorithms for automated insurance systems. However, despite these efforts, there are still certain deficiencies in attaining desirable results. This research employs a deep learning model to accurately detect and pinpoint the areas of a vehicle that have been affected by damage following an accident. The proposed model, utilizing the CNN framework, aims to accurately detect and identify damaged components in an outdoor setting. Once the model correctly identifies these damaged parts, it will promptly contact the company to initiate the insurance process, following effective training. Users simply need to upload a photograph of a car that has sustained damage, and this technology will accurately identify the specific damaged components and promptly inform the insurance company.

The key contributions to our work are as follows:

- The proposed model can significantly reduce time in insurance claims process.
- A dataset has been prepared by collecting manual shot images from real-life damaged cars, which tends to be useful in detecting damages after accidents.
- Several deep learning models have been tested with our custom dataset to achieve the highest accuracy among them and the model that is able to reach the highest accuracy is "IncetionV3" of which the accuracy is 97%.

II. LITERATURE REVIEW

Recently, feature engineering-based machine learning models have improved motor insurance fraud detection. The authors of [4] extend our knowledge-based approach to incorporate computer vision and natural language processing to construct an Auto Insurance Multimodal Learning (AIML) framework. They next assess the model's performance with multi-modal data vs the baseline model with only structural data and use AIML to detect auto insurance fraud using real-world data. AIML includes a visual data processing framework and the self-designed Semi-vehicle Feature Engineer (SAFE) for car insurance data analysis. The findings show that AIML improves the model's fraud detection compared to structural data-only models.

Vehicle damage is a rising liability for shared mobility operators. Due to the amount of driver handovers, a precise and fast inspection system that can spot tiny damages and classify them is needed. [5] creates a damage detection model to discover and classify car damages into twelve classes. Deep learning algorithms and transfer learning and training methods are used to improve detection performance. The final model can recognize tiny faults in damp and muddy conditions after being trained on over 10,000 damage photographs. A domain expert performance review found the model comparable. A specially built light street is utilized to evaluate the model, showing that high reflections hinder detection.

Picture recognition can detect automotive damage. Insurance companies, rental firms, and auto repair shops might benefit from this method for diagnosing and assessing car exterior damage. Licensees and used car sellers have historically had trouble reporting car damage and calculating penalties. Deep learning and neural networks were utilized to develop an architectural model of Mask R-CNN that calculates car damage [7]. We use a deep feature prediction network to segment damaged auto parts precisely. This project extends business technology to detect and quantify car scratches to help the used car market and auto rental organizations. It will eliminate intermediaries and allow car dealerships to price and insure more fairly. The Mask-RCNN model has 93% accuracy. The proposed research uses a customized dataset of damaged car photographs from various settings with precise labeling and annotation for image segmentation.

Traditional claim forecasting fits claim frequency and severity to a probability distribution function to predict future claims. The study suggests a new insurance claim prediction method [8]. They add two new variables—weather and car sales—to forecast the quarterly average insurance claim per insured car. Second, they use SVM, Decision Trees, Random Forests, and Boosting. Finally, they identify the biggest insurance claim predictors. Their 2008–2020 dataset comes from an Athens-based insurance provider's car portfolio. They found that minimal temperature of Elefsina, one of Athens' meteorological stations, with a 3-quarter lag, and new car sales with 3-quarter and 1-quarter lags are the most informative predictors. The top models were XGBoost on the 15 most important variables and Random Forest with limited depth.

An upgraded Mask R-CNN method was used to automatically detect, identify, and categorize traffic incident automobile damage in [9]. Object detection research benefits greatly from this strategy. They recognized and categorized a damaged car image using deep learning, mask R-CNN, instance segmentation, and transfer learning. Additionally, a web-based claim estimator can automatically locate and assess damage using user-supplied pictures. Additionally, three pre-trained models were used to accelerate convergence: Inception, ResNetV2, VGG-16, VGG-19. Finally, comparative performance evaluations use accuracy, precision, recall, F1 score, loss function, and confusion matrices for the three pre-trained models. The proposed method automatically locates and classifies car damage using empirical data, satisfying the study's goal. Mask-R CNN and pre-trained Initiation ResNetV2 outperform other models in discovery, localization, and severity-damaged execution.

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.

III. Proposed Methodology

In this section we are going to elaborate the proposed methodology for our work which includes data collection, data cleaning, preprocessing, model training and evaluation. Diagram of the overall methodology is shown in Figure 1 and every steps of the methodology is further discussed in the following subsections.

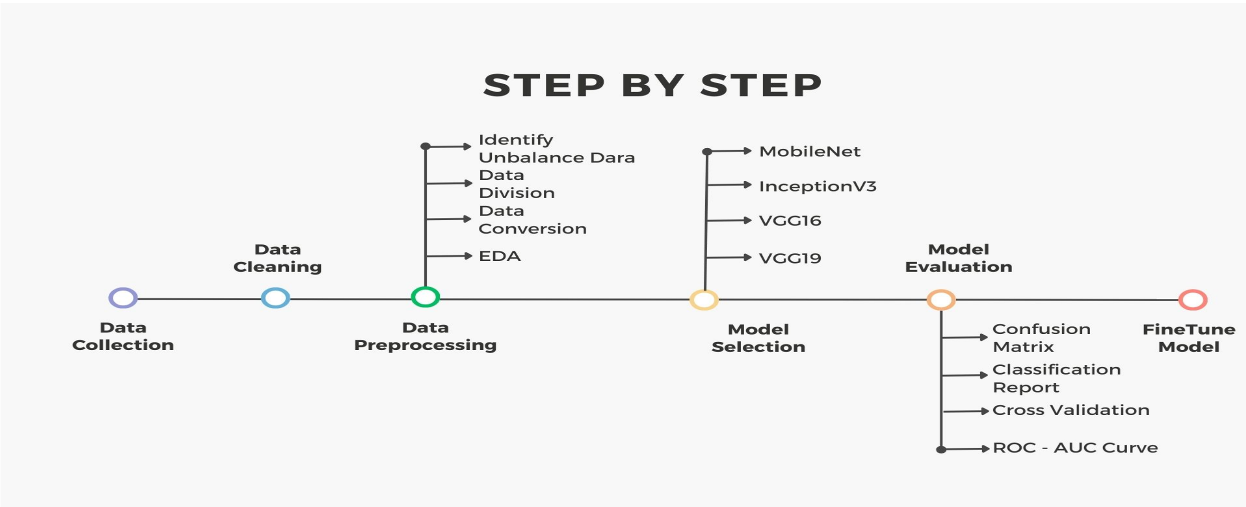

Figure 1: Proposed Methodology of the work

A. Data Collection

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 pictures. Altogether 5121 images were collected for five different damage categories namely "Crack", “Scratch”, “tire flat”, “glass shatter”, and “lamp broken”. Sample images of different classes are shown in figure 2.

B. Dataset 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.

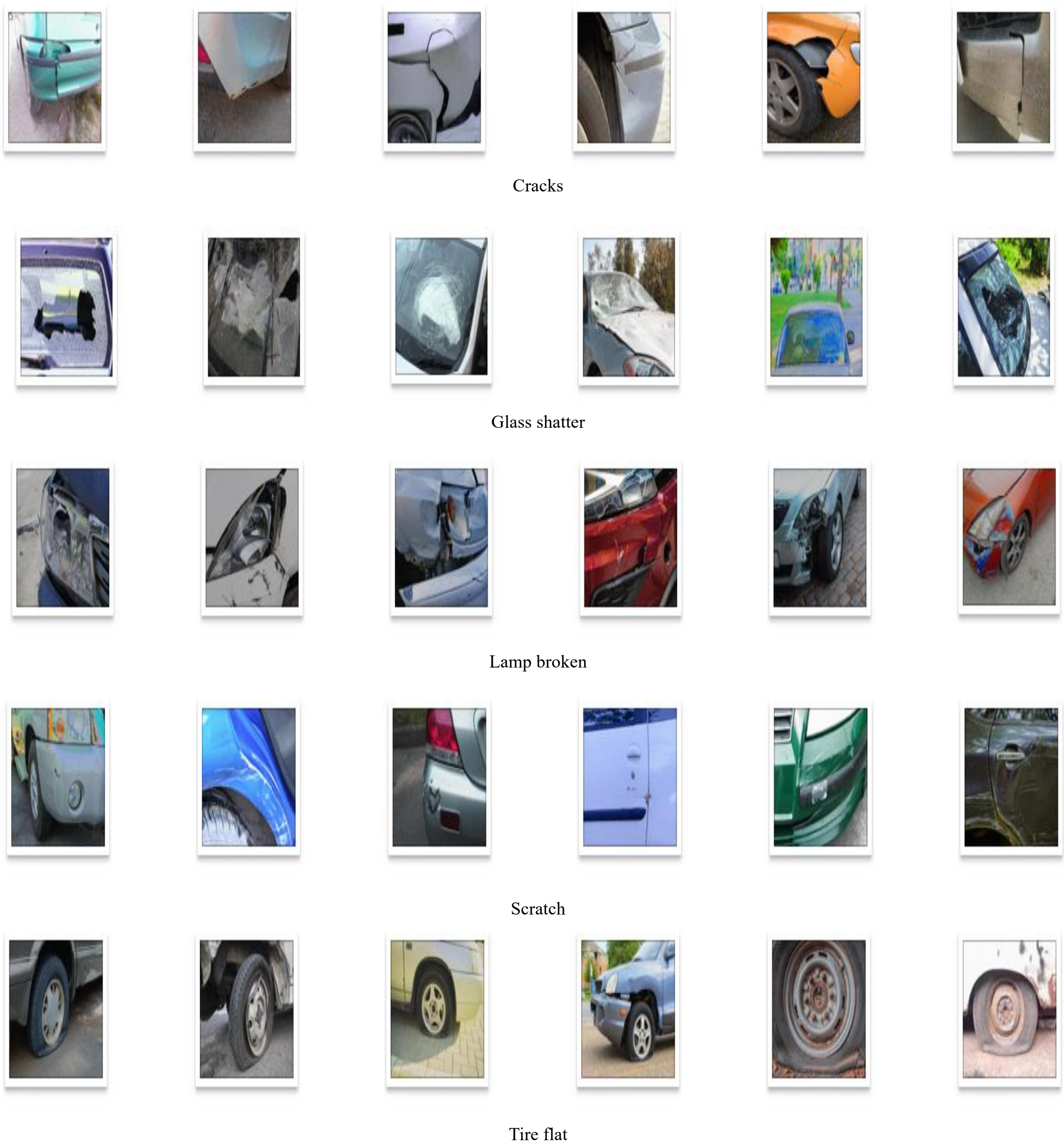

Figure 2: Sample images of different kinds of damages

C. Split Dataset

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.

D. 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.

MobileNet:

Because of its effectiveness and small architecture, MobileNet is a great option for identifying damage to the car image. Because of its lightweight architecture, MobileNet 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, MobileNet's features may be adjusted to provide precise damage identification on the particular damage vehicle dataset. All things considered, MobileNet is a strong contender for this purpose because of its effectiveness and versatility.

ResNet:

Because of its deep architecture and exceptional performance in image classification tasks, ResNet, also known as Residual Network, is a great option for identifying damages in a damaged photo. By including skip connections, ResNet 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 ResNet models provide a solid foundation, allowing for effective fine-tuning on the damage vehicle dataset. ResNet 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.

Depth-wise Separable Convolutions

The term “Depthwise Separable Convolution” alludes to a channel whose profundity and spatial measurements may be isolated, hence the word “separable”. Depthwise Distinguishable Convolution partitions the calculation into two stages, as opposed to conventional convolution, which does the channel-wise and spatially-wise preparation in one step. A single convolutional channel is connected to each input channel amid depthwise convolution, and the result of depthwise convolution is at that point combined directly, utilizing pointwise convolution.

Linear Bottlenecks

The concept of linear bottlenecks is persuaded by two highlights. On the one hand, it is obvious that the comparison parcel of the input space (*x*) is compelled to make a straight change in the event that a layer's result takes the frame of ReLU (*Bx*) and the result remains non-zero (*Bx*). In other words, the profound systems can, as it were, utilize a direct classifier on the yield domain's non-zero volume locale. On the other hand, at whatever point ReLU collapses a channel, information in that channel is unavoidably misplaced. This misfortune happens for the passing on ReLU issue. Passing on the ReLU issue can be portrayed as a circumstance where a parcel of neurons produces zero yield. Tall learning rate and huge negative inclination are the reasons for the biting the dust ReLU issue. Real-life data has numerous confinements and a predisposition nearly all the time, which makes the biting the dust ReLU issue, which eventually causes unavoidable information misfortune. According to the contentions, a direct change is adequate to store all of the pertinent information on the off chance that the input space can be implanted into a low dimensional space, whereas utilizing ReLU as an enactment works. To do this, convolution blocks might incorporate linear bottleneck layers, as shown in Table 1.

TABLE I. BOTTLENECK RESIDUAL BLOCK TRANSFORMING FROM K TO K' CHANNELS, WITH STRIDES, AND EXPANSION FACTOR.

Input	Operator	Output
*h * w * k*	1*1 conv2d, ReLU	*h * w * (tk)*
*h * w * tk*	3*3 dwise s=s, ReLU	*hs * ws * (tk)*
*hs * ws * (tk)*	linear 1*1 conv2d	*hs * ws * k^{-1}*

Inverted Residuals

The bottleneck squares take after the remaining squares in that they both begin with an input, go through a number of bottlenecks, and conclude with an extension. The two factors/aspects are fundamentally dependable for the easy routes that may be introduced between different bottlenecks to extend the slope engendering capacities in multiplier layers: (1) about all of the data is contained within the bottlenecks. (2) with a non-linear tensor change, the extension layer can be seen as an execution detail. Also, compared to the routine structure, utilizing the altered engineering (modified leftover) is more memory productive.

Architecture of the fine-tuned InceptionV3 model

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 shows the InceptionV3 building piece with the subtle elements of change counting, bottleneck input, yield, and operations.

IV. RESULT ANALYSIS

A. Evaluating Models

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 MobileNet 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 is another noteworthy feature. Table 2 shows the Precision, F1 score and Accuracy of each model.

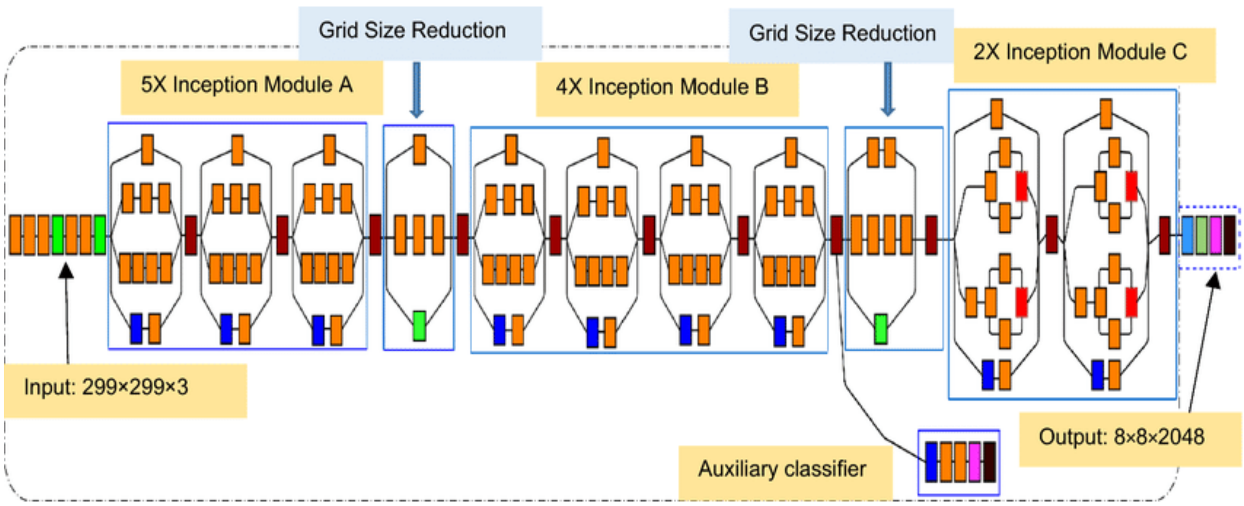

Figure 3: InceptionV3 Architecture

TABLE II. EVALUATION OF THE VARIOUS DEEP LEARNING MODELS

DL Model	Training Accuracy	Validation Accuracy	F1 Score	Precision	Accuracy
VGG16	96.58%	93.18%	88%	92%	93%
VGG19	95.65%	93.18%	87%	95%	93%
ResNet50	91.58%	80.90%	75%	88%	83%
InceptionV3	**98.56%**	**96.10%**	**95%**	**96%**	**97%**
MobileNet	97.29%	90.84%	85%	95%	91%

Table 2 shows that among all the models InceptionV3 achieved the best F1 score, precision and the best accuracy. Confusion matrix of the best model is shown in figure 4.

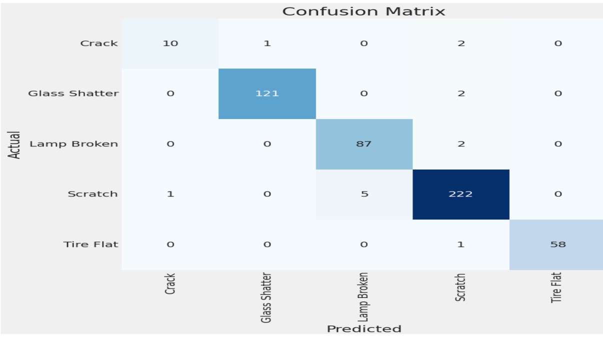

Figure 4: Confusion matrix of the best model

The confusion matrix was created to assess the effectiveness of our suggested network. It concentrated the outcomes of our model's predictions following a successful training phase. True positives, true negatives, false positives, and false negatives are often represented by four distinct values in the confusion matrix. These four components from a confusion matrix table allow us to determine the model's accuracy and precision. The matrix demonstrates 10 correct predictions of Crack out of 11 images, 121 correct predictions of Glass Shatter out of 122 images, 87 correct predictions of Lamp Broken out of 92 images, 222 correct predictions of Scratch out of 229 images and 58 correct predictions of Tire Flat out of 58 images. The generated confusion matrix is reported in Figure 3. An accuracy curve according to epochs is presented in Figure 5 to clearly understand our model's performances.

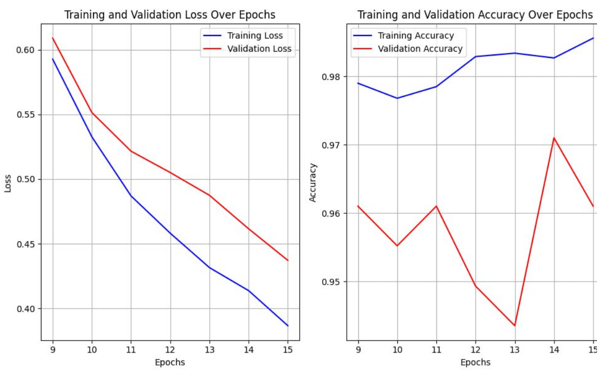

Figure 5. Accuracy Curve according to Epochs for fine tuned InceptionV3

Among convolutional neural network designs, such as ResNet, MobileNet, 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.

B. 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 3.

TABLE III. COMPARISON OF PERFORMANCES 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	

V. CONCLUSION AND FUTURE WORK

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.

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