International Journal Software Engineering and Computer Science (IJSECS) 3 (3), **2023, 324-333**
Published Online December 2023 in IJSECS (http://www.journal.lembagakita.org/index.php/ijsecs)
P-ISSN : 2776-4869, E-ISSN : 2776-3242. DOI: https://doi.org/10.35870/ijsecs.v3i3.1784.

Revolutionizing Automotive Parts Classification Using InceptionV3 Transfer Learning

Djarot Hindarto *
Informatics Study Program, Faculty of Communication and Informatics Technology, Universitas Nasional, City of South Jakarta, Special Capital Region of Jakarta, Indonesia.
Email: djarot.hindarto@civitas.unas.ac.id

Received: 31 October 2023; Accepted: 20 November 2023; Published: 10 December 2023.

Abstract: This study presents a novel methodology for classifying automotive parts by implementing the Transfer Learning technique, utilizing the InceptionV3 architecture. We use a proprietary dataset encompassing diverse categories of automotive components for training and evaluating the model. The experimental findings demonstrate that this approach attains a performance accuracy level of 93.78% and a loss rate of 0.2938. The efficacy of InceptionV3 Transfer Learning in addressing the intricacies associated with automotive parts classification is demonstrated through its utilization of pre-existing knowledge from diverse domains. The resultant model reflects a capacity to accurately discern spare parts, thereby enhancing the efficiency of the automotive inventory management process. Utilizing InceptionV3 Transfer Learning in this scenario yields a notable and favorable outcome, thereby revolutionizing the traditional framework of automotive parts categorization. The model's efficacy in enhancing the efficiency and accuracy of automotive inventory management is evidenced by its achievement of a notable precision level and a minimal loss rate. The implications of these findings are significant in addressing intricate classification challenges within the automotive industry. They pave the way for utilizing intelligent technologies to optimize parts identification and management processes. This study establishes a foundation for a novel approach to comprehending and applying categorization systems for automotive components. This is achieved by harnessing the capabilities of Transfer Learning using the InceptionV3 model.

Keywords: Automotive Components; Classifying; InceptionV3; Performance Accuracy; Transfer Learning.

1. Introduction

The automotive industry has experienced substantial growth in recent decades due to the widespread implementation of cutting-edge technologies, including autonomous vehicles and progressively advanced connectivity systems. Even with this, the industry continues to confront substantial obstacles concerning the organization and categorization of automotive components. Traditional classification systems are no longer deemed sufficient for managing an ever-increasing variety of complex components, as they tend to be less effective at accurately identifying various components. Considering this, adopting an innovative strategy to surmount these challenges is critical. A potentially practical approach involves implementing transfer learning, specifically targeting models like InceptionV3. By capitalizing on the expertise, a model has acquired in prior endeavors, transfer learning enables it to develop and adjust to novel datasets rapidly. InceptionV3 [1], a model that has demonstrated efficacy in classifying complex images, presents a prospective resolution for enhancing the efficiency and precision of automotive parts classification.

The classification of automotive parts is assuming greater significance considering contemporary vehicles' proliferation and variety of components. Conventional classification systems frequently need to help discern intricate design variations or subtle visual distinctions, potentially resulting in inaccuracies during inventory management and customer service. Transfer learning with InceptionV3 [2] is anticipated to surmount this challenge by enhancing the model's precision in identifying and categorizing components. By implementing transfer learning in the classification of automotive components, this study offers renewed optimism for increased productivity and accuracy. This will facilitate the advancement of spare parts management systems that are more complex while also enabling the incorporation of artificial intelligence technologies within the automotive sector. Consequently, this novel methodology not only addresses the present-day obstacles but also propels the progression of the automotive sector toward a future characterized by enhanced connectivity, efficiency, and adaptability.

The significance of categorizing automotive parts is growing urgently due to the proliferation and variety of components in contemporary vehicles. The proliferation of spare parts into circulation introduces intricacy into supply chain management, inventory control, and customer support operations. Improper utilization of a classification system may give rise to inaccuracies concerning the quantity and presence of spare parts, thereby impeding the ability to manage inventory and satisfy customer service requirements effectively. Conventional classification systems frequently encounter difficulties when identifying components that exhibit visual similarity or possess intricate design variations. This deficiency may lead to erroneous grouping, impeding the service process and potentially resulting in inventory management errors. Consequently, a more sophisticated and adaptable strategy is required to address the difficulties of automotive parts classification. Integrating sophisticated methodologies, including transfer learning, with InceptionV3 models presents a potentially fruitful resolution for enhancing the precision and effectiveness of automotive component identification and classification. By capitalizing on the insights acquired by models from extensive datasets, transfer learning can assist classification systems in identifying components with intricate visual variations with incredible speed and accuracy. Therefore, this methodology facilitates enhanced inventory management and elevates customer service standards by guaranteeing the punctual accessibility of necessary spare parts in a constantly evolving automotive sector.

This study provides an overview of advancements in classifying automotive parts by implementing transfer learning, focusing on the InceptionV3 [3] model. Due to its exceptional feature extraction capability across various hierarchical levels, InceptionV3 was selected as a prospective tool to enhance the precision of automotive component classification substantially. Through integrating transfer learning and artificial intelligence principles, this study offers novel resolutions to the progressively intricate obstacles associated with the classification of automotive parts. The InceptionV3 model is anticipated to identify a wide range of automotive components efficiently and precisely by utilizing the insights it has acquired from prior datasets. The results of this study are expected to make a valuable contribution to the advancement of automotive parts management systems, improving their reliability and efficiency, as well as enhancing the precision of classification. Using part-recognition models can improve the efficiency of parts management systems, enabling automotive companies to deliver prompt and effective responses to customer demands. In its entirety, this study aims to not only advance classification technology but also significantly enhance the operational efficiency and dependability of automotive parts management. Through the utilization of transfer learning and InceptionV3, this study advances the application of artificial intelligence in the context of the evolving dynamics of the contemporary automotive sector.

The research methodology employed in this study entails the acquisition of a comprehensive dataset encompassing a diverse range of automotive components. Subsequently, the dataset will be partitioned into two subsets: one designated to train the InceptionV3 model and the other to evaluate its performance. Throughout the training procedure, the model will undergo adjustments employing transfer learning methodologies to exploit the knowledge acquired by InceptionV3 from the vast ImageNet dataset [4]. During model testing, a comparative analysis will be conducted between the classification outcomes of the InceptionV3 model that has undergone training and conventional classification methods. The model's effectiveness in classifying automotive parts will be evaluated using performance metrics such as accuracy, precision, and recall. Furthermore, the evaluation will encompass intricate design variations to gauge how transfer learning can enhance the model's efficacy in discerning visual distinctions among comparable elements. By presenting this novel approach, this research will likely contribute substantially to the comprehension and execution of enhanced categorization methods for automotive components. This, in turn, will propel the automotive industry towards a more contemporary and automated trajectory. In this instance, the research inquiry that emerges is as follows: What is the comparative performance of the InceptionV3 model in utilizing transfer learning for automotive parts classification in contrast to conventional classification methods? What is the research question? To what degree can the application of transfer learning using InceptionV3 enhance the precision and efficacy of classifying automotive components characterized by intricate design variations? What is the second research question?.

2. Research Method

2.1 Dataset Automotif

The automotive dataset utilized in this study was obtained from Google image sources [5], encompassing visual depictions of 14 categories of automotive components. The diverse characteristics of modern vehicles indicate the intricate composition of their components. The dataset includes various components, from engine parts to interior elements, comprehensively depicting different facets within the automotive domain. The dataset exhibits multiple variations, which signifies the extensive array of components that necessitate identification and categorization within automotive parts management. The visual characteristics of each part category show distinct variations in design and shape, posing a challenge when attempting to classify them using conventional systems. Hence, the dataset's inclusion of 14 different types of components presents a formidable obstacle that aligns with the intricacies of the contemporary automotive industry. The dataset source for this study was selected as Google image source due to its extensive availability and diverse range of images accessible on the platform. Including various lighting conditions, viewing angles, and other common variations encountered in real-world environments expands the dataset's coverage. Using datasets from Google Images [6] can enhance the model's proficiency in accurately identifying and categorizing automotive components within contexts that closely resemble real-world scenarios. This study demonstrates the practical and contextual considerations in training automotive parts classification models by collecting a dataset from Google Images. The presence of diversity within the dataset provides a solid basis for teaching the model, enhancing its ability to handle visual variations that may arise in real-world scenarios effectively. Hence, utilizing this automotive dataset is crucial for the model's evaluation and advancement. Moreover, it accurately represents the multifaceted and intricate nature of the automotive industry, necessitating attention to accomplish the transfer learning objectives outlined in this study.

2.2. Convolutional Neural Network

Convolutional Neural Networks (CNN) [7] are architecturally tailored to tackle image processing challenges and comprehend the spatial organization inherent in visual data. The CNN architecture draws inspiration from the human nervous system's layer-by-layer neuronal processing of visual information. The convolution layer, which utilizes kernels or filters to extract features from the input image, is a fundamental component of a CNN. By means of this convolution process, CNN can comprehend a hierarchical structure of features, from basic details like edges to more intricate characteristics like textures or abstract patterns. Following this, a pooling layer is implemented to decrease the spatial dimension of the convolution outcomes, thereby streamlining the training procedure, and reducing the number of parameters. Furthermore, CNN possesses the benefit of automated feature extraction, obviating the need for intricate manual feature extraction processes. CNN models can autonomously adjust to a diverse range of image-processing tasks, obviating the need for laborious manual modifications. Primarily, the efficacy of CNNs is attributed to their capacity to acquire progressively intricate feature representations as the network depth expands; this enables the model to comprehend abstract and contextual data gradually.

Convolutional Neural Networks, which have numerous real-world applications such as face detection, image segmentation, and object recognition, are fundamental to the development of computer vision technology. The accomplishment of these tasks by CNN demonstrates not only its expertise in image processing but also its pivotal contribution to the emergence of significant breakthrough prospects in digital image processing. An instance of CNN's notable practical implementation involves identifying and classifying objects within images. Convolutional Neural Networks demonstrate exceptional performance in object recognition, even in complex scenarios. They naturally understand and analyze object characteristics and patterns at various abstraction levels. This facilitates the implementation of artificial intelligence technology to classify and identify objects in real-life scenarios.

Additionally, concerning image segmentation, CNN can distinguish and label particular regions within the image. This is particularly advantageous in medical processing, where Convolutional Neural Networks can accurately determine and isolate individual cells or organ structures within medical images. This presents an opportunity to leverage computer vision technology to facilitate expedited and precise medical diagnoses. Face detection is yet another application that demonstrates CNN's prowess. CNNs can comprehend facial features in a hierarchical fashion, enabling them to accurately detect and identify faces, even when confronted with intricate lighting circumstances or varying viewing angles. This concept facilitates the advancement of security applications, personal identification, and human-machine interaction systems that are more intuitive in nature. CNNs not only offer a structure for constructing models for computer vision tasks, but they also showcase the effectiveness of a hierarchical method for extracting features, leading to significant revelations in visual data analysis. CNN supports the swift progressions in computer vision and image processing as this technology continues to evolve. This support has far-reaching beneficial effects that span numerous sectors, including health, security, and human-machine interaction.

2.2. InceptionV3

The Inception Layer is composed of the output filter banks of the preceding layers (1×1 Convolutional layer, 3×3 Convolutional layer, 5×5 Convolutional layer) concatenated into a single output vector that serves as the input for the subsequent stage.

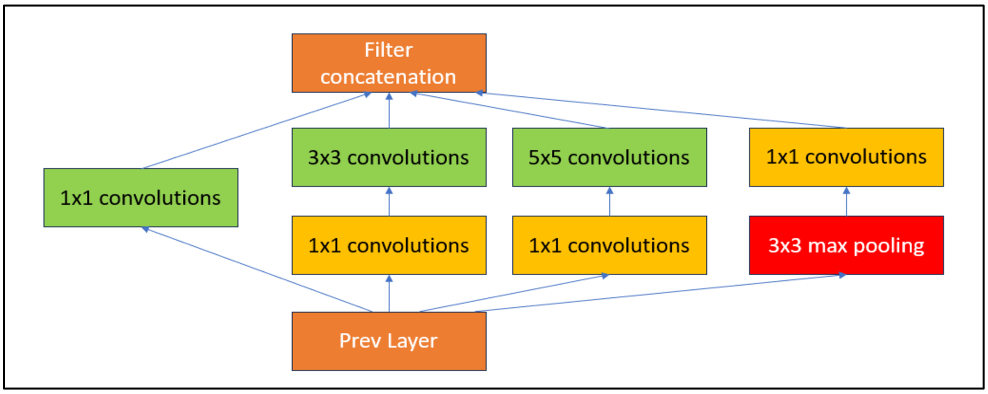

Figure 1. Inception Layer

Figure 1, the diagram, or visual representation denoted as Figure 1 generally depicts the structure of an Inception layer integrated into a convolutional neural network. The GoogleNet model added the Inception layer, which is known for its creative use of parallel filter sizes to pick up features at different sizes. Let's dissect the components mentioned above:

1) Prev Layer: This denotes the neural network architecture's preceding layer. The output of the previous layer determines the input to the Inception layer.
2) The Inception layer is characterized, in part, by its implementation of 1x1 convolutions. By means of these convolutions, the input's dimensionality is decreased, and crucial linear combinations of features are captured. They function as a means of reducing dimensionality and improving computational efficiency.
3) A 3x3 max pooling operation is utilized to reduce the resolution of the spatial dimensions of the input through down sampling. This operation reduces the computational load while preserving the most essential characteristics.
4) An additional set of convolutions, this time with a filter size of 3x3, is implemented to capture more intricate patterns and structures present in the data. By operating concurrently with the 1x1 convolutions, these convolutions enable the network to acquire knowledge of features across various scales.
5) Similarly, convolutions employing a larger filter size (5x5) are utilized to capture structures and patterns within the input data that are even more substantial. By executing distinct filter sizes in parallel, the network is capable of efficiently acquiring knowledge of hierarchical characteristics.
6) Filter concatenation is performed along the depth dimension on the outputs obtained from the various operations (1x1 convolutions, 3x3 max pooling, 3x3 convolutions, 5x5 convolutions). By combining features obtained from different filter sizes, the neural network can acquire a wide range of knowledge, thereby improving its capacity to depict intricate patterns within the input data.

To summarize, the Inception layer parallelizes the application of 1x1 convolutions, max pooling, and convolutions with varying filter sizes. By implementing this architecture, the network can capture features at various scales, which enhances the model's overall performance in image recognition tasks and facilitates more efficient feature learning. The InceptionV3 algorithm is a product of evolutionary progress from its predecessor, InceptionV2, and, in a broader sense, from the Convolutional Neural Network (CNN) architecture. Google Research devised the algorithm discussed herein with the purpose of addressing intricate image processing tasks, including but not limited to image classification and object detection. The InceptionV3 model is widely recognized for its capacity to extract features across multiple hierarchical levels, enabling a more comprehensive understanding of visual data structures. One of the primary advancements in InceptionV3 pertains to the incorporation of the Inception module, initially introduced in InceptionV1, and subsequently refined to achieve a more sophisticated iteration. The Inception module employs the principle of feature extraction parallelism through the incorporation of convolution filters with diverse dimensions, spanning from 1x1 to 3x3. This methodology enables the model to concurrently extract information from various levels of abstraction, thereby enhancing its ability to handle intricate variations in image data effectively.

Moreover, the InceptionV3 model [8] incorporates the utilization of Average Pooling prior to the classification layer. The primary objective of this approach is to decrease the dimensionality of the data space and mitigate the risk of overfitting, consequently enhancing the model's ability to generalize when presented with novel data. This decision demonstrates a strategic approach aimed at improving the precision of the model when dealing with extensive and intricate datasets. InceptionV3 is renowned for its implementation of the Regularization Dropout technique, which involves the random exclusion of specific units or nodes within the network during the training phase. The implementation of this approach serves to mitigate the issue of overfitting, enhances the long-term viability of the model, and guarantees its increased adaptability to fluctuations within the dataset. The significance of InceptionV3 resides in its capacity to address intricate computational challenges by leveraging the Inception module and the Regularization Dropout technique. The success of the system can be attributed to its exceptional capability in accurately performing image classification tasks. This makes it a highly suitable option for a wide range of applications within the field of image processing. Notably, it can be effectively utilized in the creation of transfer learning models for tasks such as automotive parts classification, as well as other tasks that require comprehensive visual analysis. InceptionV3 is considered a significant milestone in the advancement of image processing algorithms, as it paves the way for the creation of more sophisticated models that can effectively handle the growing intricacy of visual data.

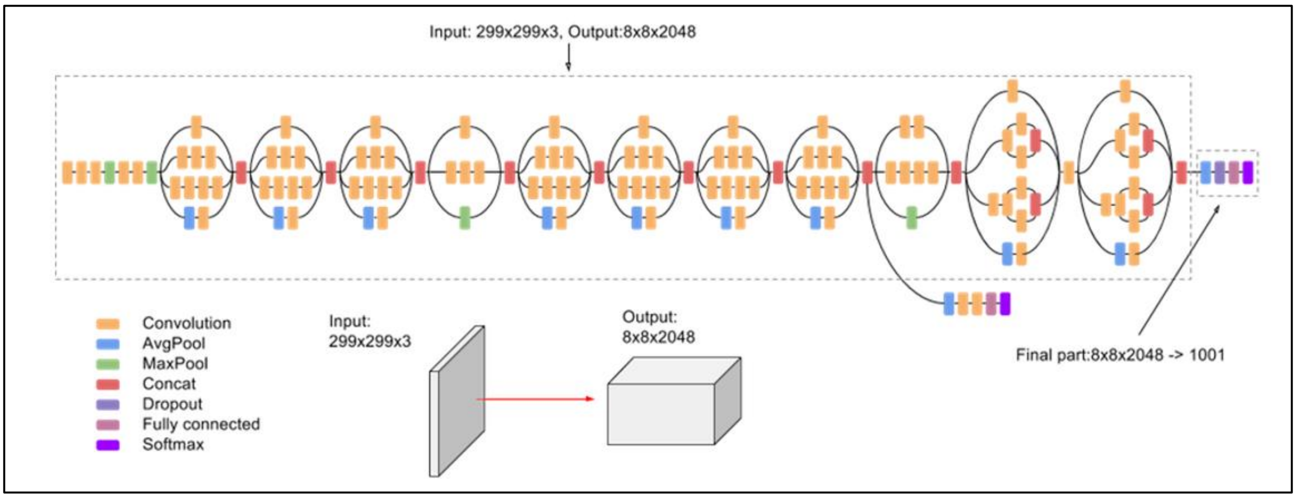

Figure 2. InceptionV3 Architecture [9]

In Figure 2, the InceptionV3 model, which is a Convolutional Neural Network [10] renowned for its ability to tackle intricate image processing tasks, is structured with multiple layers that culminate in an output of dimensions 8x8x2048. The initial step involves utilizing an input image with dimensions of 299x299x3, where three channels are employed to represent the RGB color model. The present model exhibits a higher level of complexity in comparison to its predecessors, namely InceptionV1 and V2, as it incorporates a total of 42 layers. The initial stage commences with the utilization of a Convolution layer, wherein convolution filters are employed to process the input image and extract features across various hierarchical levels. Subsequently, the process of Average Pooling and Max Pooling is used to decrease the spatial dimensions of the extracted features. This approach aids in diminishing the quantity of parameters and mitigating the risk of overfitting, consequently enhancing the efficacy of the model. Concatenation layers are employed in deep learning models to merge the outputs of preceding layers. This enables the model to effectively leverage information from diverse sources, thereby enhancing its comprehension of the image at a more comprehensive and profound level. Subsequently, a Dropout layer is employed to mitigate the risk of overfitting by stochastically disregarding a subset of units or nodes during the training process. The subsequent stage encompasses the utilization of the Fully Connected layer, wherein all nodes are interconnected to process the features that were previously extracted. Subsequently, the model undergoes training utilizing the softmax function to obtain class probabilities as the output. The ultimate result of the model exhibits dimensions of 8x8x2048, which signifies that it has successfully amalgamated and harnessed information from all input images to generate a more abstract representation of features. Despite having 42 layers, InceptionV3 exhibits a remarkable level of efficiency. The intricate architectural design of this model enables it to attain exceptional levels of accuracy in tasks related to image classification. InceptionV3 offers a comprehensive and efficient approach to addressing the intricacy of visual data in the field of image processing through the integration of diverse methodologies, including pooling, concatenation, and dropout.

3. Result and Discussion

3.1 Results

Research into the classification of images of automotive spare parts using the InceptionV3 model demonstrates significant success in addressing the challenge posed by visual differences between the parts. The model achieved a respectable level of accuracy in classifying automotive components across 14 classes by employing transfer learning techniques in InceptionV3. The experimental results first demonstrate the high accuracy with which InceptionV3 can identify and differentiate between different auto parts. The model can extract relevant high-level features from images of parts with complex designs because it uses the InceptionV3 architecture, which has been trained on large and diverse datasets. This suggests that utilizing pre-trained models for transfer learning can significantly contribute to enhancing model classification abilities in niche areas like automotive components. After that, we dive deeper into the model's efficacy by discussing things like which components InceptionV3 has the easiest time recognizing and which it has the most trouble with. The potential benefits and drawbacks of this transfer learning approach are also discussed, especially regarding the model's ability to generalize to differences in design and image quality. To provide a complete picture of the model's efficacy in automotive parts classification applications, this study may also address crucial aspects like training time, dataset size, and hyperparameter selection. The purpose of this whole discussion is to shed light on how the InceptionV3 model helped boost classification precision and speed for auto components. These findings and discussion provide a foundation for expanding the use of AI in the automotive sector, particularly in the management of spare parts and the introduction of cutting-edge new components.

3.2. Dataset Automotive Image

Automobile components are fundamental constituents that assemble the framework and functionality of an automobile. This category comprises a variety of automotive components that are critical for ensuring the vehicle's optimal operation and dependability. The components consisting of the clutch function to establish and sever power connections between the engine and transmission; the cylinder, which is an essential element of the combustion system; the shock absorber or shocker, responsible for mitigating vibrations and ensuring vehicle stability; and the spark plug, which generates a flame to ignite the air-fuel mixture within the engine combustion chamber. In contrast, gears such as spur gears and helical gears are utilized to convert torque and velocity between shafts. Filters are components that aid in maintaining clean air or fluid throughout a vehicle's system. A fuel tank, as its name implies, is a receptacle utilized for the storage of fuel. Automotive parts also consist of bevel gears, bearings, and rack-pinions, all of which are critical for power transmission and facilitating the motion of other components. As an element of the combustion mechanism, the piston oscillates in the cylinder of the engine as it performs the process of combustion. Additionally, as regulators of fuel and airflow into the engine, valves play a vital function. Wheels are an additional critical component that establishes a connection between the vehicle and the road surface, thereby ensuring traveler comfort, stability, and control. By acquiring knowledge and identifying these diverse automotive components, vehicle proprietors and technicians can uphold the vehicle's peak performance, perform scheduled maintenance, and guarantee the vehicle's safe operation. The use of visualizations built from photos of auto parts found on Google Images could speed up the process of locating, understanding, and servicing those parts. Thus, a comprehensive comprehension of these diverse components is crucial for guaranteeing the vehicle's efficiency and sustainability under both routine transportation and severe operational circumstances.

Rich and varied in appearance, the 689 image files, which are categorized into fourteen classes of automotive parts, depict a wide range of vehicle components. Every type corresponds to a distinct category of the component, encompassing a multitude of facets of the automotive system. The images in each class offer a comprehensive examination of the specific attributes and visual distinctions that exist among automotive components. The clutch, cylinder, spark plug, spur gear, filter, fuel tank, bevel gear, bearing, helical gear, piston, rack-pinion, valve, and wheel are all included in these classes of vital components. Every category corresponds to a distinct function and role within the complete vehicle system, including power transmission, combustion components, the control system, and the wheels of the vehicle. The process of categorizing images into these fourteen classes enhances comprehension regarding the visual composition and design variations of specific automotive components. This enables the application of classification technology, specifically transfer learning in conjunction with the InceptionV3 model, to identify and categorize these components accurately. Subsequent investigations and advancements in the classification of automotive parts have become more targeted and concentrated on the distinct visual attributes of each category, thereby promoting comprehension and effectiveness in the management of automotive parts.

3.3. InceptionV3 Pre-Trained Model Experiment

View Model Summary & Plot

```
In [33]:  1  # Viewing the summary of the model
          2  model.summary()

Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 inception_v3 (Functional)   (None, 8, 8, 2048)        21802784

 global_average_pooling2d (  (None, 2048)              0
 GlobalAveragePooling2D)

 dropout (Dropout)           (None, 2048)              0

 dense (Dense)               (None, 1024)              2098176

 dense_1 (Dense)             (None, 14)                14350

=================================================================
Total params: 23915310 (91.23 MB)
Trainable params: 2112526 (8.06 MB)
Non-trainable params: 21802784 (83.17 MB)
```

Figure 3. InceptionV3 View Model

Figure 3, the InceptionV3 View Model, shows the CNN's architecture. InceptionV3, developed by Google, is known for image classification efficiency and accuracy. The diagram shows convolutional layers, batch normalization, and auxiliary classifiers sequentially. InceptionV3 uses inception modules with different filter sizes and global average pooling to reduce dimensionality before the final fully connected layer. The complex design lets the network capture diverse features at different scales, promoting robust feature learning and image recognition success.

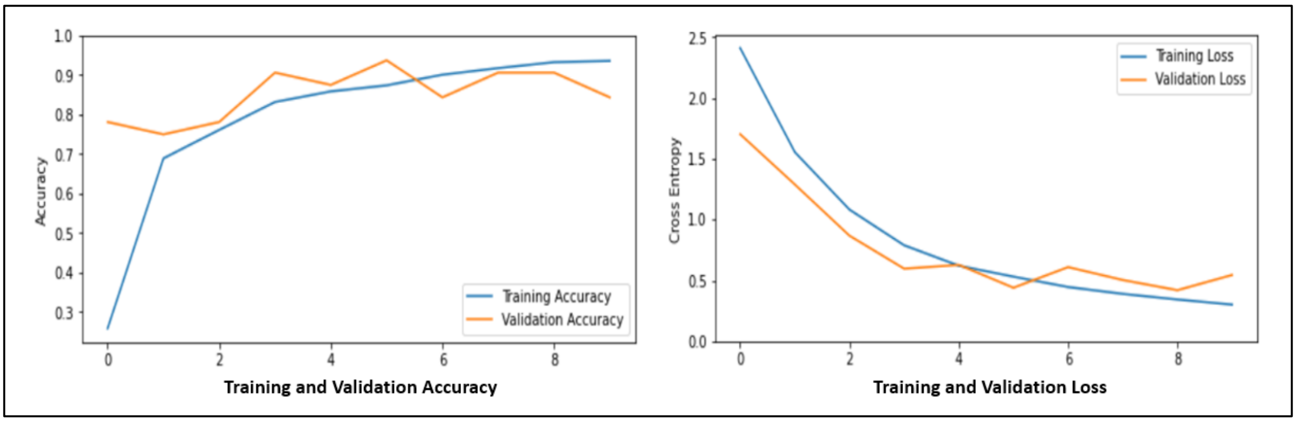

Figure 4. InceptionV3 Performance

InceptionV3, shown in Figure 4, had a good loss of 0.2938 and an accuracy of 93.78%. Losses indicate the model's predictive errors during training, with lower values indicating better performance. Additionally, the model's 93.78% accuracy metric highlights its instance classification accuracy. These results show that InceptionV3 is a good image classification algorithm because it minimizes errors and makes accurate predictions. The model's high accuracy rate offers its ability to capture complex data patterns and features, boosting its real-world success.

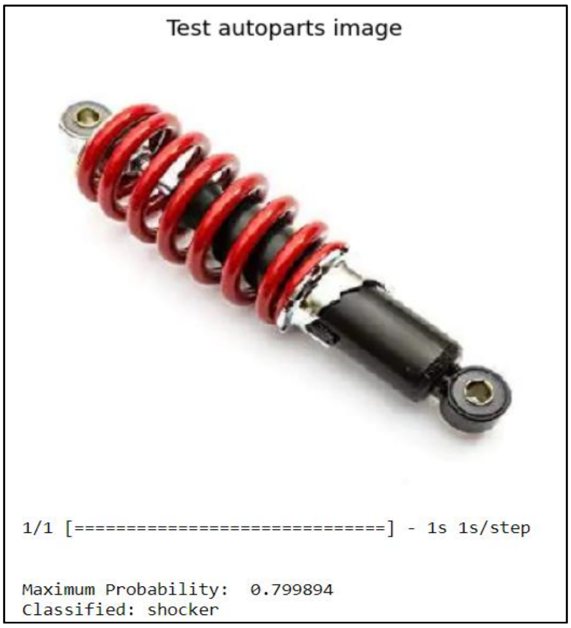

Figure 5. Testing shocker

The maximum probability of 0.799894 in Figure 5, "Testing Shocker," is intriguing. With high confidence, the model classifies the input as a "shocker." With 0.799894 as the maximum probability value, the model's prediction is confident. This suggests that the model correctly classifies the input as a "shocker." In applications where precision and confidence in classification are crucial, such reliable predictions demonstrate the model's robustness in correctly identifying and categorizing instances, especially in the "shocker" class.

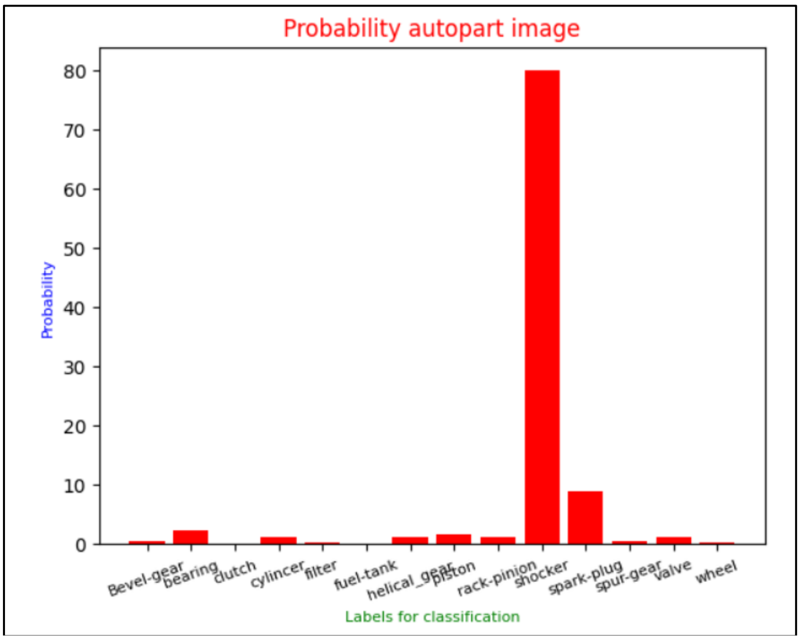

Figure 6. Probability shocker

Figure 6, a bar graph of the probability distribution for the "shocker" and "auto parts" classes, shows the model's classification confidence. The diagram shows the model's probabilities for the "shocker" and "auto parts" classes. The bars' heights represent class probability scores. Analyzing this graph shows the relative likelihood of the input being a "shocker" or "auto parts." Visualizations help explain the model's decision-making process and evaluate real-world predictions for specific classes.

3.4. Discussion

What is the comparative performance of the InceptionV3 model in utilizing transfer learning for automotive parts classification in contrast to conventional classification methods? (Research Question 1)

There are notable distinctions in the effectiveness of the InceptionV3 model in leveraging transfer learning for the classification of automotive parts, as compared to conventional classification methods. In the realm of transfer learning, InceptionV3 distinguishes itself through its capacity to exploit the acquired knowledge derived from vast image datasets, such as ImageNet. The utilization of this technique enables the model to detect intricate and diverse characteristics of automotive components rapidly and precisely. On the other hand, traditional classification techniques frequently need to be revised when it comes to effectively addressing design variations and visual disparities among different components. These models might exhibit reduced capability in extracting pertinent features from images depicting parts with elevated complexity and variability. Hence, while conventional methods may yield satisfactory outcomes in specific situations, the distinct benefit of InceptionV3 lies in its capacity to effectively accommodate greater complexity and intricate visual variations within datasets pertaining to automotive parts. InceptionV3 offers the added advantage of mitigating the potential issue of overfitting, particularly in scenarios where the available dataset is constrained in size. Transfer learning models can generalize more effectively and yield improved outcomes, even when confronted with limited data, by capitalizing on the knowledge acquired from prior tasks. In the domain of automotive parts classification, the presence of visual variability and intricacy poses a significant obstacle. To address this challenge, the utilization of transfer learning with InceptionV3 has emerged as a promising method to enhance the overall accuracy of classification more dependably and efficiently.

What degree can the application of transfer learning using InceptionV3 enhance the precision and efficacy of classifying automotive components characterized by intricate design variations? (Research Question 2)

The utilization of transfer learning with InceptionV3 has a notable influence on enhancing the precision and efficacy of classifying automotive components that exhibit intricate design variations. The InceptionV3 model, having undergone training on extensive and diverse image datasets like ImageNet, possesses the capability to extract abstract features that are generally relevant to a wide range of visual objects, including intricate automotive components. The primary benefit of transfer learning is rooted in the capacity of InceptionV3 to leverage the knowledge it has acquired from prior tasks and apply it to the specific task of classifying automotive parts. Through this approach, the model can enhance its ability to adjust to intricate design variations rapidly, comprehend nuanced visual disparities, and discern distinctive characteristics among different components. Hence, in scenarios where conventional classification methods struggle to handle diverse design variations, the utilization of transfer learning with InceptionV3 can yield enhanced accuracy levels in the classification of automotive parts. The utilization of InceptionV3 can improve the efficacy of classification by mitigating the issue of overfitting, particularly in scenarios characterized by a scarcity of training data. Models that have undergone training using extensive datasets, such as ImageNet, possess the capability to extract general features that are applicable across various visual scenarios. This characteristic helps mitigate the risk of the model excessively adapting to specific training data, thereby enhancing its capacity to identify pertinent features on automotive components with diverse designs. The subject matter at hand is intricate and multifaceted. The utilization of transfer learning with InceptionV3 can enhance the precision and effectiveness of automotive parts classification models, particularly when confronted with the difficulties posed by intricate design variations. This approach enhances the model's capacity to classify components effectively and facilitates the broader application of artificial intelligence technology in the automotive sector. Consequently, it supports the advancement of more advanced parts management systems that can adapt to changing market demands.

4. Related Work

Classification using the InceptionV3 model can start with the latest artificial neural network image recognition and classification advances. Multi-scale convolution and innovative modules have helped InceptionV3, a fundamental Inception architecture, perform well in image classification tasks. InceptionV3 may have outperformed other methods in complex object recognition, overfitting, and classification accuracy. InceptionV3's innovative approach has spurred extensive research into sophisticated and reliable image classification models. ADSI-2019 reported 11,000 fires in India in 2019. This article builds a deep-learning image-based fire and smoke detector. Inception-V3 [11] is modified for smoke-filled fire images. The new optimization function reduces computation costs. Therefore, the Inception V3-based model produces the best results with fewer false positives than previous studies. Businesses need sentiment analysis to understand customer opinions, improve relationships, and use emotional marketing. This study analyzes image sentiment using Inception-v3, a robust deep-learning algorithm. The method under consideration exhibits superior performance compared to conventional machine learning approaches. (99.5% accuracy) using CK+, FER2013, and JAFFE datasets, making it applicable across business domains [12]. This study developed an algorithm to automatically detect cataracts using adaptive images and an Inception-v3 CNN model. This algorithm achieves high classification accuracy (95%) by using images from various sources, including anterior segment media images. This project has cost-effective potential and can detect specific items [13]. VI-NET classifies copy-move forgery-manipulated images using deep learning. VI-NET links model results to convolution layers using VGG16 and Inception V3 deep learning architectures. VI-NET outperformed transfer learning and machine learning models with 99% classification accuracy using the COMOFOD dataset and cross-validation protocol. Experimentally, this model outperforms other deep learning architectures [14]. Inception V3 classifies leaf diseases, and Random Forest detects soil fertility in this rice plant pest and disease model. Over 98% of diseases are predicted with 97% and 96% accuracy and precision, surpassing previous models. The study also shows a cost-effective plant disease detection method [15].

5. Conclusion

The research Revolutionizing Automotive Parts Classification Using InceptionV3 Transfer Learning concludes that the utilization of transfer learning, specifically with the InceptionV3 model, yields highly favorable outcomes in the classification of automotive parts. The model attained an accuracy rate of 93.78% and a loss rate of 0.2938 when trained on a dataset comprising 14 distinct categories of spare parts. The findings of this study demonstrate that the utilization of InceptionV3 significantly enhances the ability to classify automotive components, thereby providing empirical evidence for the efficacy of transfer learning in this domain.

References

[1] de Zarzà, I., de Curtò, J. and Calafate, C.T., 2022. Detection of glaucoma using three-stage training with EfficientNet. *Intelligent Systems with Applications*, *16*, p.200140. DOI: https://doi.org/10.1016/j.iswa.2022.200140.

[2] Ahmed, M., Afreen, N., Ahmed, M., Sameer, M. and Ahamed, J., 2023. An inception V3 approach for malware classification using machine learning and transfer learning. *International Journal of Intelligent Networks*, *4*, pp.11-18. DOI: https://doi.org/10.1016/j.ijin.2022.11.005

[3] Zhou, Z., Song, Z., Fu, L., Gao, F., Li, R. and Cui, Y., 2020. Real-time kiwifruit detection in orchard using deep learning on Android™ smartphones for yield estimation. *Computers and Electronics in Agriculture*, *179*, p.105856. DOI: https://doi.org/10.1016/j.compag.2020.105856.

[4] Tan, M. and Le, Q., 2019, May. Efficientnet: Rethinking model scaling for convolutional neural networks. In *International conference on machine learning* (pp. 6105-6114). PMLR. DOI: https://doi.org/10.2310/8000.2013.131108.

[5] Baker, P. and Collins, L., 2023. Creating and analysing a multimodal corpus of news texts with Google Cloud Vision's automatic image tagger. *Applied Corpus Linguistics*, *3*(1), p.100043. DOI: https://doi.org/10.1016/j.acorp.2023.100043.

[6] Kim, Y., Li, D., Xu, Y., Zhang, Y., Li, X., Muhlenforth, L., Xue, S. and Brown, R., 2023. Heat vulnerability and street-level outdoor thermal comfort in the city of Houston: Application of google street view image derived SVFs. *Urban Climate*, *51*, p.101617. DOI: https://doi.org/10.1016/j.uclim.2023.101617.

[7] Iswahyudi, I., Hindarto, D. and Santoso, H., 2023. PyTorch Deep Learning for Food Image Classification with Food Dataset. *Sinkron: jurnal dan penelitian teknik informatika*, *8*(4), pp.2651-2661. DOI: https://doi.org/10.33395/sinkron.v8i4.12987.

[8] Joshi, K., Tripathi, V., Bose, C. and Bhardwaj, C., 2020. Robust sports image classification using InceptionV3 and neural networks. *Procedia Computer Science*, *167*, pp.2374-2381. DOI: https://doi.org/10.1016/j.procs.2020.03.290.

[9] Sam, S.M., Kamardin, K., Sjarif, N.N.A. and Mohamed, N., 2019. Offline signature verification using deep learning convolutional neural network (CNN) architectures GoogLeNet inception-v1 and inception-v3. *Procedia Computer Science*, *161*, pp.475-483. DOI: https://doi.org/10.1016/j.procs.2019.11.147.

[10] Hindarto, D., 2023. Enhancing Road Safety with Convolutional Neural Network Traffic Sign Classification. *Sinkron: jurnal dan penelitian teknik informatika*, *8*(4), pp.2810-2818. https://doi.org/10.33395/sinkron.v8i4.13124.

[11] Biswas, A., Ghosh, S.K. and Ghosh, A., 2023. Early Fire Detection and Alert System using Modified Inception-v3 under Deep Learning Framework. *Procedia Computer Science*, *218*, pp.2243-2252. DOI: https://doi.org/10.1016/j.procs.2023.01.200.

[12] Meena, G., Mohbey, K.K. and Kumar, S., 2023. Sentiment analysis on images using convolutional neural networks based Inception-V3 transfer learning approach. *International Journal of Information Management Data Insights*, *3*(1), p.100174. DOI: https://doi.org/10.1016/j.jjimei.2023.100174.

[13] Faizal, S., Rajput, C.A., Tripathi, R., Verma, B., Prusty, M.R. and Korade, S.S., 2023. Automated cataract disease detection on anterior segment eye images using adaptive thresholding and fine tuned inception-v3 model. *Biomedical Signal Processing and Control*, *82*, p.104550. DOI: https://doi.org/10.1016/j.bspc.2022.104550.

[14] Kumar, S., Gupta, S.K., Kaur, M. and Gupta, U., 2022. VI-NET: A hybrid deep convolutional neural network using VGG and inception V3 model for copy-move forgery classification. *Journal of Visual Communication and Image Representation*, *89*, p.103644. DOI: https://doi.org/10.1016/j.jvcir.2022.103644.

[15] Meenakshi, M. and Naresh, R., 2022. Soil health analysis and fertilizer prediction for crop image identification by Inception-V3 and random forest. *Remote Sensing Applications: Society and Environment*, *28*, p.100846. DOI: https://doi.org/10.1016/j.rsase.2022.100846.