Fuzzy Integral Based Ensemble Approach for Car Damage Detection Using Transfer Learning
CSE 598 Group 14 Project Report

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Abstract

In car insurance, evaluation durations after accidents vary, presenting challenges. Our AI model aims to aid insurance companies by providing accurate evaluations. It integrates transfer learning models and fuzzy ranking into an ensemble model. If performance is suboptimal, we use explainability methods to ensure accuracy by bridging the gap between robust and explainable systems.

1 Introduction

Reporting car accidents to insurance companies often involves lengthy evaluation processes for assessing damage. Speeding up this evaluation would benefit both car owners and insurers, especially the latter. Current evaluation methods conducted by insurance employees may lead to biases. Hence, a robust solution is needed to address these issues.

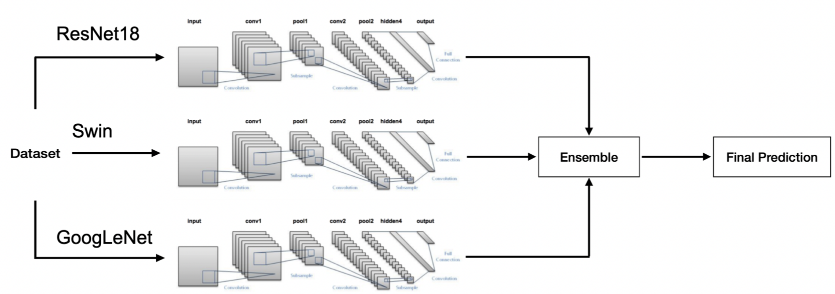

Figure 1: Model Architecture

We propose using an AI model to speed up evaluations for both insurance companies and car owners. Our model combines transfer learning models into an ensemble learning approach, using dynamic Fuzzy ranking to reduce biases. This integrated model guarantees reliable evaluation results.

2 Methodologies

We start with a car damage dataset featuring six damage categories. Three framework models (GoogLeNet, ResNet18, Swin) are trained on this dataset. Their outputs feed into an ensemble model, which uses dynamic fuzzy ranking to counter biases in each model. This method, utilizing a modified Gompertz function, enhances bias mitigation.

The dataset originally sourced from Kaggle, `https://www.kaggle.com/datasets/imnandini/analytics-vidya-ripik-ai-hackfest` , comprises six categories representing different types of damages: crack, dent, shattered glass, scratch, flat tire, and broken lamp.

2.1 Transfer learning Model

Transfer learning leverages a pre-trained model from one task to enhance performance on a related task. This accelerates learning and yields superior results compared to training from scratch, especially with limited data or similar tasks. Inductive transfer involves different source and target tasks, where the source task imparts general knowledge to the target task. Transductive transfer applies a model trained on source data to target data of the same task.

2.1.1 ResNet-18

Key Architectural Features:

- Residual Connections: ResNet18 incorporates "skip connections" or residual connections that bypass certain layers, allowing gradients to flow more efficiently and mitigating the vanishing gradient problem [1].
- Bottleneck Design: It utilizes bottleneck layers that compress feature maps before applying convolutional filters, reducing the number of parameters and computational cost.
- Depth: With 18 layers, ResNet18 strikes a balance between depth and efficiency, achieving high accuracy without being overly complex.

2.1.2 GoogleNet

Key Architectural Features:

- Inception Modules: These modules consist of parallel convolutional filters of different sizes (1x1, 3x3, 5x5) and a max-pooling layer, capturing features at multiple scales simultaneously.
- Auxiliary Classifiers: Additional classifiers are added at intermediate layers, providing auxiliary loss signals and improving gradient flow.
- Global Average Pooling: This technique replaces fully connected layers, reducing the number of parameters and preventing overfitting [2].

2.1.3 Swin

Key Architectural Features:

- Hierarchical Transformer: Swin-Transformer adopts a hierarchical structure that processes features at multiple scales, capturing both local and global information effectively [3].
- Window-based Attention: It utilizes window-based attention mechanisms that focus on local patches within a window, reducing computational complexity while maintaining accuracy.
- Shifted Windowing: Swin-Transformer employs shifted windowing techniques to enhance information exchange between different windows, improving feature representation.

While all three models excel at image classification, they possess distinct characteristics that make them unique. Ensemble learning, by combining these models, leverages their individual strengths to achieve superior classification performance.

2.2 Fuzzy Ranking and Ensemble Framework

The traditional ensemble method assigns equal importance to classification scores from constituent models using fixed weights. In contrast, our proposed fuzzy-rank-based ensemble approach dynamically considers each base classifier's prediction scores for every test case, resulting in improved classification without the need for weight adjustments across datasets.The equation to understand the function is: f(t) = $ae^{-e^{b-ct}}$.

Here, 'a' represents the asymptote, 'b' determines displacement along the x-axis, 'c' scales the y-axis, and 'e' denotes Euler's Number. Figures 2 display the Gompertz function [4] graphs with varying values for 'a', 'b', and 'c'.

In our method, we utilize a redesigned version of this function. We consider N as the number of constituent models, where each image in the test split of the database is associated with N prediction scores. Given that we employ three transfer learning CNN models, N equals 3.

Fuzzy ranks are generated by considering the prediction scores of each class for each given sample data. Specifically, for the lth class, the fuzzy ranks attributed to the nth constituent model are determined using the following formula:

$$R_l^{(n)} = (1 - e^{-e^{-2 \cdot S_l}}) \quad \forall l, n; \quad n = 1, 2, ..., N; \quad l = 1, 2, ..., L \tag{1}$$

The next 3 equations are utilized to compute the Fuzzy Ranks (FRS_l) and the complement of the confidence factor sum ($CCFS_l$) for class l. If label l does not belong to the top K classes, penalty values P_{R_l} and P_{CF_l} are applied to the corresponding class. The final predicted class for data instance X is determined by multiplying the FR_l and CCF_l values and selecting the minimum value among all classes.

class(X) = $\min \{FRS_l \times CCFS_l\} \quad \forall l = 1, 2, \ldots, L$

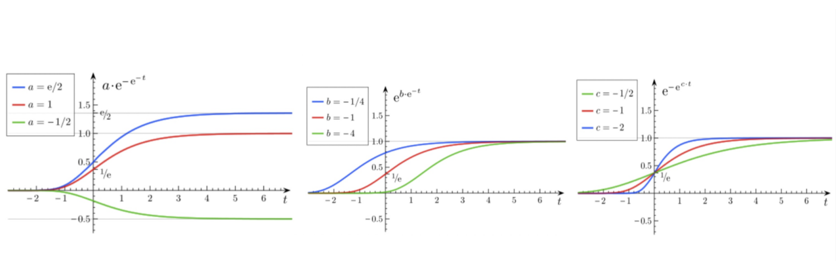

Figure 2: Gompertz Plot with variable a, b and c respectively.

2.3 Explainability

In our project, explainability is vital for improving the interpretability of our car damage detection system, especially for stakeholders like car insurance companies. We utilize GradCAM, a popular technique, to reveal the rationale behind decisions made by individual transfer learning models. By highlighting key areas in images, GradCAM explains the model's classifications, aiding user understanding. However, applying GradCAM to ensemble results is challenging due to the mathematical complexity of the ensemble model.

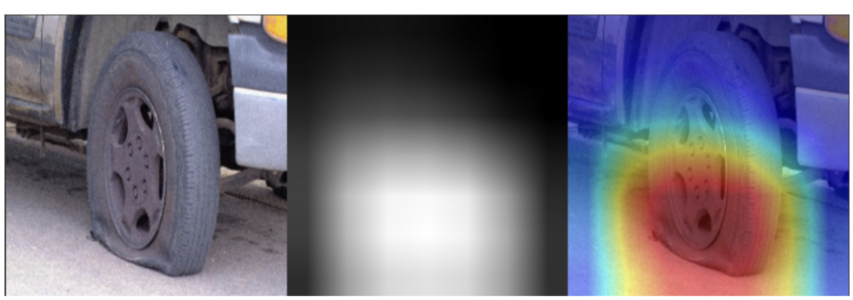

Figure 3: Exaplinability Results

3 Result

We choose Precision, Recall, and F1 scores as evaluation metrics due to our dataset's imbalanced sample distribution. Next, we'll compare our ensemble framework with baseline Transfer Learning models, integrating both deep learning and machine learning classifiers.

Model	**ResNet18**	**GoogleNet**	**SwinTiny**	**Ensemble**
Accuracy	0.905	0.931	0.746	**0.940**

Table 1: Comparative study of the performance of constituent and ensemble model.

To evaluate our ensemble model's classification performance visually, we use the receiver operating characteristic curve (ROC curve). Initially designed for binary classification, we adapt it for multi-class classification using the One vs All method. This curve measures the model's class differentiation ability, and its area indicates class classification accuracy. Plotting True Positive Rate against False Positive Rate provides insights into performance across different classes.

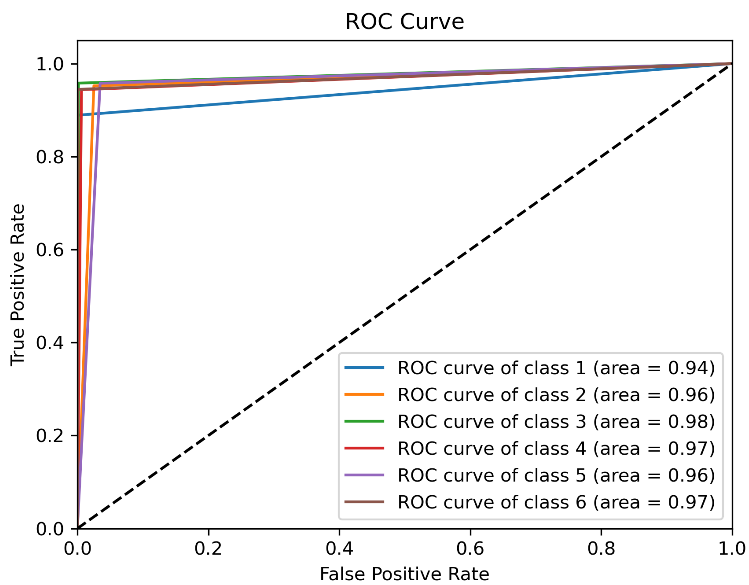

Figure 4: Ensemble model ROC-AUC Curve

4 Future Scope

Our project suggests potential research and development directions in key areas. Firstly, investigating explainability techniques for ensemble models shows promise. Additionally, tackling multi-label predictions is crucial for real-world applicability, as images may contain multiple types of damage. Future efforts could enhance our framework to accommodate multi-label predictions, enhancing system versatility and accuracy across various scenarios.

References

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[2] Szegedy, C., Liu, W., Jia, Y., Sermanet, P., Reed, S., Anguelov, D., Erhan, D., Vanhoucke, V., & Rabinovich, A. (2014, September 17). Going Deeper with Convolutions. arXiv.org. https://arxiv.org/abs/1409.4842

[3] Liu, Z., Lin, Y., Cao, Y., Hu, H., Wei, Y., Zhang, Z., Lin, S., & Guo, B. (2021, March 25). Swin Transformer: Hierarchical Vision Transformer using Shifted Windows. arXiv.org. https://arxiv.org/abs/2103.14030

[4] Wikipedia contributors. (2024, March 3). Gompertz function. Wikipedia. https://en.wikipedia.org/wiki/Gompertz_function

Individual Contribution

Team Member's Contribution			
Name	**Contribution**	**Percentage**	**Sign**
Shreya Krishna	• Doing Investigation on various dataset. • Investigating on various dataset. • Working on ensemble model accuracy. • Executed and got GradCam results on models. • Made the poster for final presentation.	20%	ShreyaK
Zehnaseeb Ali	• Working on multi-labeled dataset and Formated the CarDD dataset in single label dataset. • Investigating on various dataset. • Testing the LIME experiement with tensorflow. • Made the poster for final presentation. • Executed and got GradCam results on models.	20%	Zehnaseeb
Shravya Suresh	• Investigating on various dataset. • Attempted to classify CarDD using imagenet. Dimension issue because of multilabel • Trained based model for ensemble model. • Made the poster for final presentation. • Executed and got GradCam results on models.	20%	Shravya
Yao Ting Chen	• Working on multi-labeled dataset. • Training based model for ensemble model. • Made the poster for the final presentation. • Present the final and progress presentation • Successfully implemented Lime on Resnet using tensorflow.	20%	Ricky
Karam Kumar Sahoo	• Formated the ImageNet dataset in single label dataset. • Investigating on various dataset. • Training based model for ensemble model. • Assemble all models and create ensemble structure and gaining result. • Made the poster for final presentation.	20%	Karam kumar Sahoo

Figure 5: Individual contribution