J. Comput. Struct. Eng. Inst. Korea, 37(4)
pp.225 ~232, August, 2024
https://doi.org/10.7734/COSEIK.2024.37.4.225

pISSN 1229-3059 eISSN 2287-2302
Computational Structural
Engineering Institute of Korea

복합 적층판의 딥러닝 기반 파괴 모드 결정

무하마드 무자밀 아자드[1]·아타 우르 레만 샤[2]·M.N. 프라브하카르[3]·김 흥 수[4†]

[1]동국대학교 기계공학과 박사과정, [2]COMSATS 대학교 기계공학과 부교수,
[3]창원대학교 기계공학과 연구교수, [4]동국대학교 기계로봇에너지공학과 교수

Deep Learning-based Fracture Mode Determination in Composite Laminates

Muhammad Muzammil Azad[1], Atta Ur Rehman Shah[2], M.N. Prabhakar[3] and Heung Soo Kim[4 †]

[1]*Ph.D. Student, Department of Mechanical Engineering, Dongguk University, Seoul, 04620, Korea*
[2]*Associate Professor, Department of Mechanical Engineering, COMSATS University, Wah Campus, 47040, Pakistan*
[3]*Research Professor, Department of Mechanical Engineering, Changwon National University, Changwon, 51140, Korea*
[4] *Professor, Department of Mechanical, Robotics and Energy Engineering, Dongguk University, Seoul, 04620, Korea*

Abstract

This study focuses on the determination of the fracture mode in composite laminates using deep learning. With the increase in the use of laminated composites in numerous engineering applications, the insurance of their integrity and performance is of paramount importance. However, owing to the complex nature of these materials, the identification of fracture modes is often a tedious and time-consuming task that requires critical domain knowledge. Therefore, to alleviate these issues, this study aims to utilize modern artificial intelligence technology to automate the fractographic analysis of laminated composites. To accomplish this goal, scanning electron microscopy (SEM) images of fractured tensile test specimens are obtained from laminated composites to showcase various fracture modes. These SEM images are then categorized based on numerous fracture modes, including fiber breakage, fiber pull-out, mix-mode fracture, matrix brittle fracture, and matrix ductile fracture. Next, the collective data for all classes are divided into train, test, and validation datasets. Two state-of-the-art, deep learning-based pre-trained models, namely, DenseNet and GoogleNet, are trained to learn the discriminative features for each fracture mode. The DenseNet models shows training and testing accuracies of 94.01% and 75.49%, respectively, whereas those of the GoogleNet model are 84.55% and 54.48%, respectively. The trained deep learning models are then validated on unseen validation datasets. This validation demonstrates that the DenseNet model, owing to its deeper architecture, can extract high-quality features, resulting in 84.44% validation accuracy. This value is 36.84% higher than that of the GoogleNet model. Hence, these results affirm that the DenseNet model is effective in performing fractographic analyses of laminated composites by predicting fracture modes with high precision.

Keywords : *deep learning, fracture mode, composite laminates, transfer learning, DenseNet, GoogleNet*

1. Introduction

Composite laminates have found extensive implementation across various industries, including aerospace, marine, and transportation, owing to their exceptional mechanical characteristics, weight-saving capability, and outstanding design flexibility (Azad *et al.*, 2023; Rangappa *et al.*, 2022). During operational use, composite laminates may encounter intricate external loads that generate substantial local stresses, leading to micro-scale degradation and ultimately catastrophic structural fracture (Khalid and Kim, 2022; Khan and Kim, 2022). Considering the dependability and structural integrity of composite laminates, material scientists and engineers must understand their fracture mechanisms. The fracture mechanisms are commonly determined through fracture analysis which intends to evaluate the source of the fracture. The causes of the fracture are then avoided by redesigning the components through modifications in the concentration of their constituents or replacing their constituents

†Corresponding author:
Tel: +82-2-2260-8577; E-mail: heungsoo@dgu.edu
Received June 4 2024; Revised June 24 2024;
Accepted June 24 2024

with superior materials. Thus, setting up quantitative relations that provide insights into the common sources of fracture with respect to the mechanical properties. These relationships do perform well analytically but have limited success practically due to the complex orthotropic nature of composite materials (Khalid and Kim, 2019). Moreover, there exists no global approach that can identify the complex fracture modes present in laminated composite structures (Khan *et al.*, 2023).

Fractographic analysis, which involves visual inspection of the fractured surface of composite laminates, is an essential step in fracture analysis. Its purpose is to discover the surface-level attributes of the fracture mode, enabling the identification of propagation patterns and the source of the fracture (Mohammadi *et al.*, 2024). By examining the fracture surfaces of composite materials, an initial fracture analysis can be performed to identify the underlying causes. The first step in this process is macroscopic observation, which can reveal preliminary traces of the factors that led to the fracture (Chen, 2020). However, the macroscopic information regarding the fracture and behavior of the composite remains insufficient, thereby hindering the ability to determine the underlying factors that initiated the fracture. By conducting a detailed examination through the utilization of a scanning electron microscope (SEM), the microscopic process of fracture propagation is characterized, thereby facilitating the identification of the underlying factors contributing to fracture, such as matrix or fiber fracture.

These microscopic observations are generally of interest to material scientists who continuously develop new composite materials based on vast applications of composites. However, due to the orthotropic nature of these materials and their continuous expansion in numerous industries, it is tedious and time-consuming to do manual decision-making. Moreover, composite materials can have a broad range of fracture modes such as fiber breakage, fiber pull-out, multi-mode fracture, brittle matrix fracture, ductile matrix fracture, particle agglomeration, and so on, requiring materials scientists to have critical domain knowledge (Ejaz *et al.*, 2022; Prabhakar *et al.*, 2021). Meanwhile, in metallic materials automated fracture analysis has already found applications through the incorporation of intelligent computational techniques such as machine learning and deep learning. The sudden ductile, sudden brittle, and progressive fatigue fracture of metallic materials demonstrated the effectiveness of using artificial neural networks (Bastidas-Rodriguez *et al.*, 2016). Tsopanidis and Osovski used unsupervised machine learning to perform fractographic analysis of five tungsten-based alloys (Tsopanidis and Osovski, 2021). Similarly, another study performed ductile fracture analysis using different steel and aluminum-magnesium alloys (Avilés-Cruz *et al.*, 2024). Another study determined ductile, brittle, and fatigue fractures in various steel and aluminum alloys using a UNet-based deep learning model (Tang *et al.*, 2024). All these findings confirm the importance of using modern machine learning and deep learning techniques to automate the decision-making process for fractographic analysis. However, the existing studies are restricted to fracture mode identification of metallic materials. Therefore, this research is focused on fracture analysis of composite laminates which possess an excessive range of fracture modes, unlike metallic materials that generally fail in brittle, ductile, or fatigue fracture modes.

This study for the first time developed a dataset comprising various fracture modes of composite laminates and used deep learning to perform autonomous fracture analysis. The developed dataset is collected from literature consisting of five basic fracture modes in composites namely: fiber breakage, fiber pull-out, mix-mode fracture, matrix ductile fracture, and matrix brittle fracture. The data is collected and sorted based on these mentioned fracture modes. Due to limited amounts of training data, instead of developing a model from scratch, the pre-trained transfer learning models are utilized. GoogleNet and DenseNet-based transfer learning models are trained and then evaluated using various evaluation metrics to assess their feasibility in composite fracture analysis. Finally, the results of the proposed models are presented in the form of training and testing accuracy. Moreover, the models are also validated on unseen validation datasets, whose performance is validated using accuracy, precision, recall, and f1-score.

2. Materials and Methods

This section describes the details of the dataset and the proposed methodology of this study. It also introduces the transfer learning-based models used in this study.

2.1 Dataset

The dataset for the fractographic analysis includes a collection of SEM images from the published literature and additional images obtained during the fractographic analysis conducted in the following literature (Ahmad *et al.*, 2024; Azad *et al.*, 2022; Ejaz *et al.*, 2020; 2022; Li *et al.*, 2017; Prabhakar *et al.*, 2017; Shah *et al.*, 2017; 2018; Zulfiqar *et al.*, 2024). The SEM images were obtained from the fractured tensile test specimens for all cases. Thus, this study focuses on the tensile mode of fracture in composite laminates. The rationale for this choice lies in the significance of tensile properties in determining the overall strength and durability of composite materials. The fracture modes can provide different features at different magnifications. Therefore, the SEM images were collected at magnifications such as ×100, ×300 and ×500. Such diversity of data will allow the deep learning model to learn features of fracture modes at different magnifications helping improve the generalization ability of the model. The obtained data consists of 222 SEM images belonging to five fracture modes. These include three fracture modes of the fibers and two fracture modes of the matrix material. The five fracture modes are fiber breakage (FB), fiber pull-out (FP), mix-mode fracture (MMF), matrix brittle fracture (MBF), and matrix ductile fracture (MDF). The classes are defined through careful examination of SEM images based on the observed fracture mode. The representative image of each class is shown in Fig. 1. FB is defined as the fracture mode of individual reinforcing fibers within the composite laminate, leading to a significant reduction in load-bearing capacity and structural integrity. FP refers to the fracture mode where reinforcing fibers are pulled out of the matrix material, rather than breaking, resulting in a loss of load transfer efficiency and

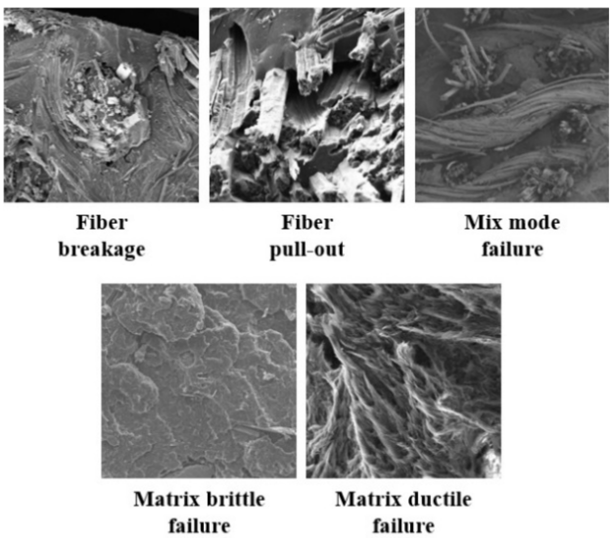

Fig. 1 The five major fracture modes present in the dataset comprising different fiber and matrix-based modes

structural strength. In MMF, multiple fracture mechanisms, such as fiber breakage, matrix cracking, and fiber pull-out, occur simultaneously or sequentially, leading to complex and uncertain degradation. MBF represents the matrix fracture where matrix material fractures in a brittle manner, resulting in the formation of cracks that compromise the composite's structural integrity. MDF refers to the fracture mode where the matrix material undergoes significant plastic deformation before fracturing, leading to energy absorption and progressive damage accumulation. Composite laminates comprise either thermosets or thermoplastic matrix materials. The obtained data comprises both matrix materials, helping characterize both MBF and MDF. Thus, incorporating both types of matrix materials and numerous fibers, this study addresses the diverse fracture modes of composites.

2.2 Transfer learning-based methodology

Deep learning models require immense amounts of data to train effectively, learn complex patterns, and achieve high-performance (Lee *et al.*, 2019). However, acquiring such extensive datasets can be challenging and resource-intensive in the current research due to the associated cost and time to conduct SEM analysis. Therefore, this research utilizes the transfer learning concept which allows deep learning models to pre-train on large general-purpose source datasets and apply them to smaller target datasets (Azad *et al.*, 2024). Thus, the transfer of knowledge concept is helpful in significantly reducing the required amount of data and computational resources, while still achieving robust and accurate results in specialized applications. This research utilizes the transfer learning concept through DenseNet and GoogleNet-based pre-trained models due to their promising performance in various computer vision tasks. The concept of transfer learning adopted in this study is shown in Fig. 2. Herein, the ImageNet data is used as the source data. ImageNet is a large-scale public dataset designed for use in visual object re-cognition research, containing millions of labeled images across thousands of categories. It is widely used for training and ben-chmarking deep learning models in image classification and other computer vision tasks. The ImageNet source data is used to pre-train the deep learning models which helps initialize their weights and pre-learn the features and patterns from image data for improved performance and faster convergence when fine-tuned on target SEM image data in a later stage.

The original DenseNet and GoogleNet models trained on ImageNet data can provide a classification of thousands of classes present in the original data. However, when utilizing this model in the target domain of SEM images, the final classification layer is removed, and a new classification layer is added based on the number of classes in the target data. Further architectural details of the pre-trained models are shown in Fig. 3.

The GoogleNet model was first developed in 2014, by researchers at Google, while its InceptionV3 variant known for its efficient architecture that combines various convolutional filter sizes through Inception modules was proposed in 2015 (Szegedy *et al.*, 2015). For the GoogleNet model, its latest InceptionV3 variant is utilized in this study. It achieves high accuracy on image classification tasks with reduced computational cost by utilizing techniques like factorized convolutions and batch normalization. InceptionV3 is widely used in computer vision applications due to its balance of depth, performance, and efficiency. The last layer of the GoogleNet model is also replaced with a global pooling layer and a five-neuron dense layer for SEM image classification. The global average pooling layer condenses each feature map to a single value by computing the average of all its elements, effectively summarizing the feature information. The five-neuron dense layer is a fully connected neural network layer with five neurons, each producing an output that typically corresponds to one of five possible classes FB, FP, MMF, MBF, and MDF.

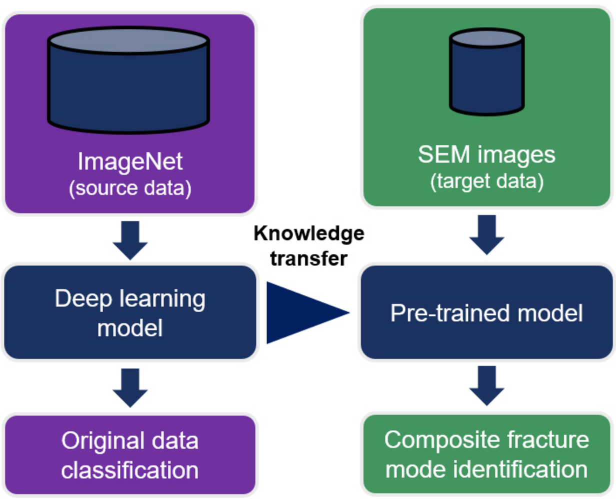

Fig. 2 The concept of transfer learning utilized in this study to overcome the limited data issue

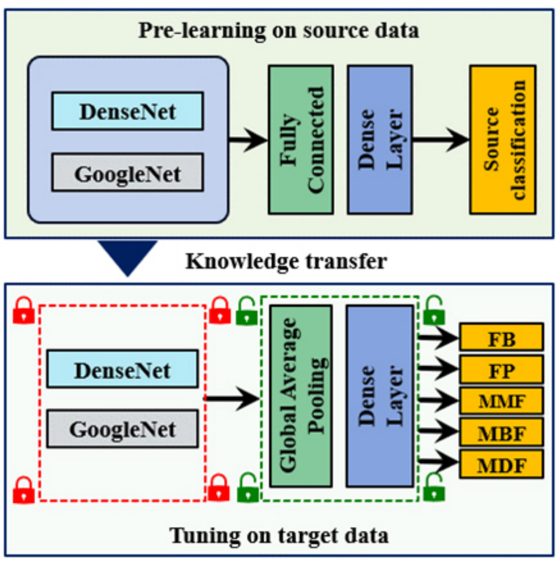

Fig. 3 The architectural details of the DenseNet and GoogleNet-based transfer learning models, showing the trainable and untrainable layers for pre-training on source data and tuning on target data

The Densely Connected Convolutional Network (DenseNet) model was developed in 2017 (Huang *et al.*, 2017), and its specific variant featuring 121 layers called DenseNet121 has been used in this study. The DenseNet model is designed to promote efficient feature reuse by connecting each layer to the next layer in a feed-forward manner helping alleviate the vanishing gradient problem. DenseNet121 is known for its high performance on image classification tasks while maintaining computational efficiency, making it a state-of-the-art choice for various computer vision applications. For this study, the last layer (classification layer) of the original DenseNet model is removed and replaced with a global pooling layer and a five-neuron dense layer. Therefore, in Fig. 3, the red locks show layers of the respective models that are trained on the source data only, while the green unlocked locks denote the trainable layers that are changed for the target SEM images dataset for fracture mode determination of laminated composites.

3. Results and Discussion

The proposed transfer learning concept for fracture mode determination of composite laminates is validated using Python programming language in Jupyter Notebook with a TensorFlow environment. Initially, the raw SEM images were pre-processed to make data suitable for the learning of the deep learning model. Generally, the SEM images obtained from the experiments contain text representing the resolution, experimental conditions, and specifications of the machine. Such information on the images can affect the learning capability of the deep learning models. Therefore, all SEM images were cropped to exclude unnecessary text and cropped to only include the region containing the fracture mode information. The pre-processed images are then split into three sets: training, testing, and validation, containing 70%, 15%, and 15% data, respectively. The training and test data are utilized to tune the pre-trained models on SEM images, and later the validation data is used to validate the developed models. All trainable parameters of both models are kept identical to compare their performance on the same datasets. Therefore, a SoftMax activation is used in the classification layer of both models. The models are trained for 40 epochs using an Adam optimizer with a learning rate of 10^{-4}. Moreover, a sparse categorical cross-entropy loss function is used during training due to multi-class classification. To provide a robust and reliable estimate of model performance, both models are developed using a 10-fold cross-validation approach. Herein, the train and test sets are combined and then divided into ten sets, where in each fold nine sets are used for training and one set is used for testing. The results from 10-fold cross-validation for the DenseNet and GoogleNet models are shown in Table 1. The training results demonstrated that both models can effectively learn the pattern and features from SEM images for each fracture mode. The DenseNet model exhibited an average training accuracy of 94.01%, and the GoogleNet model exhibited an average training accuracy of 84.55%. However, on the test data, the accuracy of both models dropped which is common in deep learning, but the drop in accuracy is significant for the GoogleNet model. This depicts that the GoogleNet model is unable to generalize well for the new data demonstrating overfitting. Moreover, the DenseNet model possesses a deeper architecture compared to the GoogleNet model, which signifies that the complexity of the fracture modes in composite laminates can't be learned well by the shallow model, and a deeper model is required to recognize the pattern for each fracture mode. Thus, the significant performance drop of GoogleNet compared to DenseNet is attributed to their architectural differences. The deeper DenseNet architecture and dense connectivity facilitate better feature reuse and gradient flow, which enhances its ability to generalize well to new data. This dense connectivity allows DenseNet to effectively utilize features learned in earlier layers, providing an inherent regularization effect that mitigates overfitting and improves generalization performance. In contrast, GoogleNet, with its more traditional deep network structure and less extensive feature reuse, struggles to achieve the same level of parameter efficiency and regularization. Therefore, the overfitting issue is more prominent in the GoogleNet model.

Table 1 Training and testing accuracies of DenseNet and GoogleNet models using 10-fold cross-validation

Folds	DenseNet		GoogleNet	
	Train accuracy (%)	Test accuracy (%)	Train accuracy (%)	Test accuracy (%)
Fold-1	93.93	88.06	84.17	59.72
Fold-2	93.95	87.50	83.49	63.89
Fold-3	93.82	66.25	84.86	48.75
Fold-4	93.58	72.50	86.24	49.72
Fold-5	94.51	68.19	81.45	50.00
Fold-6	93.66	80.56	82.80	54.17
Fold-7	93.84	76.67	85.74	57.50
Fold-8	94.38	74.41	87.12	70.00
Fold-9	94.47	63.38	86.16	36.03
Fold-10	94.00	77.35	83.45	55.00
Average	**94.01 ± 0.31**	**75.49 ± 7.93**	**84.55 ± 3.51**	**54.48 ± 8.84**

The trained models tuned on the SEM image data are saved and then validated on unseen validation data to assess their performance. For deeper insights into the performance of both models, multiple evaluation metrics have been used instead of accuracy alone. Fig. 4 compares the performance of DenseNet and GoogleNet models across four evaluation metrics: accuracy, precision, recall, and f1-score. A detailed description of the evaluation metrics can be found in the following literature (Azad and Kim, 2024). DenseNet model outperforms the GoogleNet

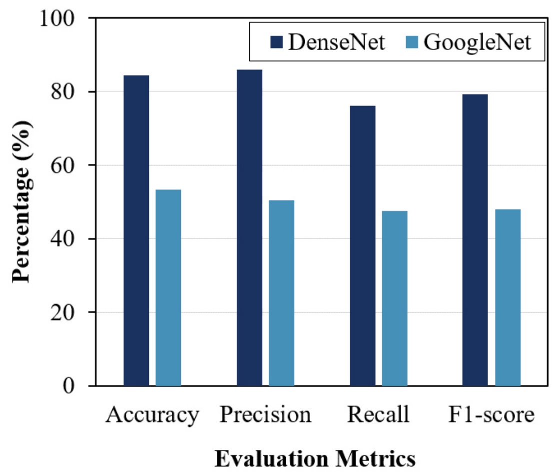

Fig. 4 The comparison of the performance of DenseNet and GoogleNet models based on various evaluation metrics

model in all metrics. Specifically, the DenseNet model achieved 84.44% accuracy, 86.06% precision, 76.13% recall, and 79.23% f1-score. In contrast, the GoogleNet model achieved only 53.33% accuracy, 50.56% precision, 47.56% recall, and 48.08% f1-score. These results suggest that DenseNet is more effective in correctly classifying the fracture mode of composite laminates even on unseen data, demonstrating better overall performance and reliability. The higher recall and F1-score indicate that DenseNet has a balanced ability to detect relevant instances and minimize both false positives and false negatives, making it a more robust model for composite fracture mode prediction. The confusion matrix for both models is shown in Fig. 5. The diagonal terms in the confusion matrix represent the accurately predicted instances, while the non-diagonal terms represent the inaccurately predicted instances. It can be observed that the DenseNet model predicted each fracture mode with higher accuracy compared to the GoogleNet model. In both models, the highest confusion is between the fiber-based failure modes and matrix-based failure modes. However, the DenseNet model has predicted the MMF with 100%, with marginal confusion between FB and FP. Additionally, the most performance drop in DenseNet is due to the confusion between the MBF and MDF. This confusion is attributed to the limited data available for these two classes, as it is difficult to obtain excessive matrix-based fracture mode images in composite laminates. Therefore, approaches like data augmentation can be used to increase the quantity of data in these two classes to improve the prediction accuracy for matrix-based failure modes.

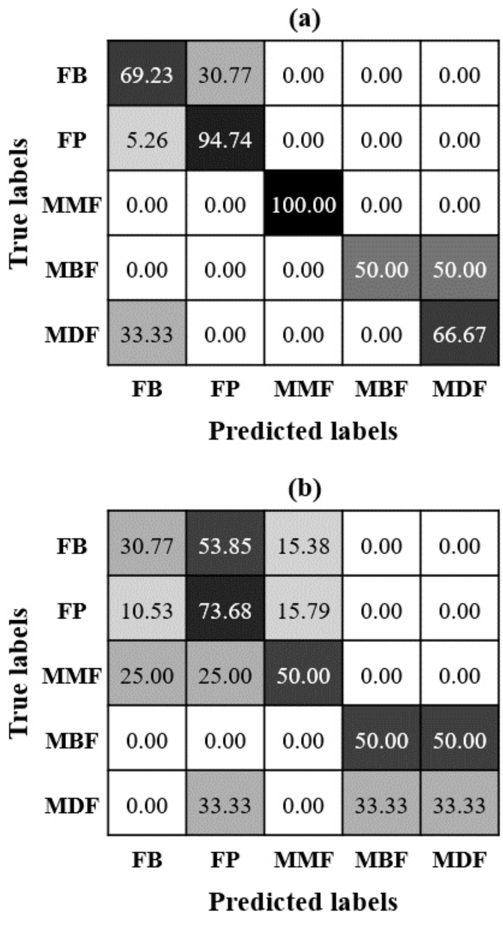

Fig. 5 The confusion matrix for the (a) DenseNet and (b) GoogleNet model

4. Conclusion

This study presents the first step in performing fracture mode identification of composite laminates using deep learning. Generally, the fracture surface analysis of laminated composites is performed by manual inspection of the SEM images of the fractured surfaces. However, this makes the process tedious and requires a lot of time and effort to identify the fracture mode. This is due to the complex modes of fiber and matrix fractures present in laminated composites, unlike the metallic materials that generally fail in ductile, brittle, or fatigue modes only. Therefore, this study proposes an autonomous fracture mode determination of laminated composites using deep learning, eliminating the need for manual inspection. The proposed approach is implemented using the transfer learning concept utilizing the pre-trained DenseNet and GoogleNet models. Both pre-trained models are developed using identical training, testing, and validation datasets. During training the DenseNet and GoogleNet models showed an accuracy of 94.01% and 84.55%, respectively. Upon validation on the unseen validation dataset, the DenseNet model showed an accuracy of 84.44%, while the accuracy of the GoogleNet model dropped significantly to 53.33%. Other evaluation metrics also demonstrated that the DenseNet model can perform well for fracture model determination of composite laminates due to its excessively deep architecture. Therefore, the proposed DenseNet model can be adopted by material scientists and engineers for autonomous fracture mode determination in novel composite laminates to expand their applications in numerous industries. However, it should be noted that there is still a possibility of further improving the performance of the models. Thus, in the future other deeper pre-trained models such as ResNet, VGG-16, VGG-19, MobileNet, and Xception can also be analyzed along with the utilization of data augmentation techniques to provide improved fracture mode determination of composite laminates. Moreover, future work can also use drop-out and other regularization techniques to reduce overfitting by adding several more layers during the fine-tuning process.

Acknowledgments

This work was supported by a National Research Foundation of Korea (NRF) grant, funded by the Korea government (MSIT) (No. 2020R1A2C1006613).

References

Ahmad, H., Shah, A.U.R., Afaq, S.K., Azad, M.M., Arif, S., Siddiqi, M.U.R., Xie, L. (2024) Development and Characterization of Kevlar and Glass Fibers Reinforced Epoxy/vinyl Ester Hybrid Resin Composites, *Polym. Compos*., 45(9), pp. 8133~8146.

Avilés-Cruz, C., Aguilar-Sanchez, M., Vargas-Arista, B., Garfias-Garcia, E. (2024) A New Machine Learning-Based Evaluation of Ductile Fracture, *Eng. Fract. Mech.*, 302, p.110072.

Azad, M.M., Ejaz, M., Shah, A.U.R., Afaq, S.K., Song, J.-I. (2022) A Bio-Based approach to Simultaneously Improve Flame Retardancy, Thermal Stability and Mechanical Properties of Nano-Silica Filled Jute/Thermoplastic Starch Composite, *Mater. Chem. & Phys.*, 289, p.126485.

Azad, M.M., Kim, H.S. (2024) Hybrid Deep Convolutional Networks for the Autonomous Damage Diagnosis of Laminated Composite Structures, *Compos. Struct.*, 329, p.117792.

Azad, M.M., Kim, S., Cheon, Y.B., Kim, H.S. (2023) Intelligent Structural Health Monitoring of Composite Structures using Machine Learning, Deep Learning, and Transfer Learning: A Review, *Adv. Compos. Mater.*,33(2) pp.162~188.

Azad, M.M., Kumar, P., Kim, H.S. (2024) Delamination Detection in CFRP Laminates using Deep Transfer Learning with Limited Experimental Data, *J. Mater. Res. & Technol.*, 29, pp.3024~3035.

Bastidas-Rodriguez, M.X., Prieto-Ortiz, F.A., Espejo, E. (2016) Fractographic Classification in Metallic Materials by using Computer Vision, *Eng. Fail. Anal.*, 59, pp.237~252.

Chen, X. (2020) Fractographic Analysis of Sandwich Panels in a Composite Wind Turbine Blade using Optical Microscopy and X-ray Computed Tomography, *Eng. Fail. Anal.*, 111, p.104475.

Ejaz, M., Azad, M.M., Shah, A.U.R., Afaq, S.K., Song, J.I. (2022) Synergistic Effect of Aluminum Trihydrate and Zirconium Hydroxide Nanoparticles on Mechanical Properties, Flammability, and Thermal Degradation of Polyester/Jute Fiber Composite, *Cellul.*, 29(3), pp.1775~1790.

Ejaz, M., Azad, M.M., Shah, A.U.R., Afaq, S.K., Song, J.I. (2020) Mechanical and Biodegradable Properties of Jute/Flax Reinforced PLA Composites, *Fibers & Polym.*, 21(11), pp. 2635~2641.

Huang, G., Liu, Z., Maaten, L. van der, Weinberger, K.Q. (2017) Densely Connected Convolutional Networks, *2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pp.4700~4708.

Khalid, S., Kim, H.S. (2019) Progressive Damage Modeling of Inter and Intra Laminar Damages in Open Hole Tensile Composite Laminates, *J. Comput. Struct. Eng. Inst. Korea*, 32(4), pp.233~240.

Khalid, S., Kim, H.S. (2022) Recent Studies on Stress Function-Based Approaches for the Free Edge Stress Analysis of Smart Composite Laminates: A Brief Review, *Multiscale Sci. & Eng.*, 4(3), pp.73~78.

Khan, A., Azad, M.M., Sohail, M., Kim, H.S. (2023) A Review of Physics-based Models in Prognostics and Health Management of Laminated Composite Structures, *Int. J. Precis. Eng. & Manuf. - Green Technol.*, 10(6), pp.1615~1635.

Khan, A., Kim, H.S. (2022) A Brief Overview of Delamination Localization in Laminated Composites, *Multiscale Sci. & Eng.*, 4(3), pp.102~110.

Lee, S.-Y., Huynh, T.-C., Park, J.-H., Kim, J.-T. (2019) Bolt-Loosening Detection using Vision-Based Deep Learning Algorithm and Image Processing Method, *J. Comput. Struct. Eng. Inst. Korea*, 32(4), pp.265~272.

Li, Z., Shah, A.R., Prabhakar, M.N., Song, J. (2017) Effect of Inorganic Fillers and Ammonium Polyphosphate on the Flammability, Thermal Stability, and Mechanical Properties of Abaca-Fabric/Vinyl Ester Composites, *Fibers & Polym.*, 18(3), pp. 555~562.

Mohammadi, R., Assaad, M., Imran, A., Fotouhi, M. (2024) Fractographic Analysis of Damage Mechanisms Dominated by Delamination in Composite Laminates: A Comprehensive Review, *Polym. Testing*, 134, p.108441.

Prabhakar, M.N., Rehman Shah, A. ur, Song, J.-I. (2017) Improved Flame-Retardant and Tensile Properties of Thermoplastic Starch/Flax Fabric Green Composites, *Carbohydr. Polym.*, 168, pp.201~211.

Prabhakar, M.N., Venakat Chalapathi, K., Atta Ur Rehman, S., Song, J. (2021) Effect of a Synthesized Chitosan Flame Retardant on the Flammability, Thermal Properties, and Mechanical Properties of Vinyl Ester/Bamboo Nonwoven Fiber Composites, *Cellul.*, 28(18), pp.11625~11643.

Rangappa, S.M., Puttegowda, M., Parameswaranpillai, J., Siengchin, S., Gorbatyuk, S. (2022) *Advances in Bio-Based Fiber: Moving Towards a Green Society*, Woodhead Publishing, p.834.

Shah, A.U.R., Prabhakar, M.N., Saleem, M., Song, J.I. (2017) Development of Biowaste Encapsulated Polypropylene Composites: Thermal, Optical, Dielectric, Flame Retardant, Mechanical, and Morphological Properties, *Polym. Compos.*, 38(2), pp.236~243.

Shah, A.U.R., Prabhakar, M.N., Wang, H., Song, J.I. (2018) The Influence of Particle Size and Surface Treatment of Filler on the Properties of Oyster Shell Powder Filled Polypropylene Composites, *Polym. Compos.*, 39(7), pp.2420~2430.

Szegedy, C., Liu, W., Jia, Y., Sermanet, P., Reed, S., Anguelov, D., Erhan, D., Vanhoucke, V., Rabinovich, A. (2015) Going Deeper with Convolutions, *2015 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, IEEE, Boston, MA, USA, pp.1~9.

Tang, K., Zhang, P., Zhao, Y., Zhong, Z. (2024) Deep Learning-Based Semantic Segmentation for Morphological Fractography, *Eng. Fract. Mech.*, 303, p.110149.

Tsopanidis, S., Osovski, S. (2021) Unsupervised Machine Learning in Fractography: Evaluation and Interpretation, *Mater. Charact.*, 182, p.111551.

Zulfiqar, A., Shah, A.U.R., Khalil, M.S., Azad, M.M., Zulfiqar, Y., Naseem, M.S., Song, J.-I. (2024) Enhancing Properties of Jute/Starch Bio-Composite Material through Incorporation of Magnesium Carbonate Hydroxide Pentahydrate: A Sustainable Approach, *Mater. Chem. & Phys.*, 314.

요 지

본 논문에서는 딥러닝을 활용하여 복합재 적층판의 파괴 모드를 결정하는 방법을 제안하였다. 수많은 엔지니어링 응용 분야에서 적층 복합재의 사용이 증가함에 따라 무결성과 성능을 보장하는 것이 중요해졌다. 그러나 재료의 이방성으로 인해 복잡하게 나타나는 파괴모드를 식별하는 것은 도메인 지식이 필요하고, 시간이 많이 드는 작업이다. 따라서 이러한 문제를 해결하기 위해 본 연구에서는 인공 지능(AI) 기술을 활용하여 적층 복합재의 파괴 모드 분석을 자동화하는 것을 목표로 하였다. 이 목표를 달성하기 위해 적층된 복합재에서 파손된 인장 시험편의 주사 전자 현미경(SEM) 이미지를 얻어 다양한 파괴 모드를 확보하였다. 이러한 SEM 이미지는 섬유 파손, 섬유 풀아웃, 혼합 모드 파괴, 매트릭스 취성 파손 및 매트릭스 연성 파손과 같은 다양한 파손 모드를 기준으로 분류하였다. 다음으로 모든 클래스의 집합 데이터를 학습, 테스트, 검증 데이터 세트로 구분하였다. 두 가지 딥 러닝 기반 사전 훈련 모델인 DenseNet과 GoogleNet을 이용해 각 파괴 모드에 대한 차별적 특징을 학습하도록 훈련하였다. DenseNet 및 GoogleNet 모델은 각각 (94.01% 및 75.49%) 및 (84.55% 및 54.48%)의 훈련 및 테스트 정확도를 보여주었다. 그런 다음 훈련된 딥 러닝 모델은 검증 데이터 세트를 활용해 검증하였다. 더 깊은 아키텍처로 인해 DenseNet 모델이 고품질 특징을 추출하여 84.44% 검증 정확도(GoogleNet 모델보다 36.84% 더 높음)를 얻을 수 있음을 확인하였다. 이는 DenseNet 모델이 높은 정밀도로 파괴 모드를 예측함으로써 적층 복합재의 파손 분석을 수행하는 데 효과적이라는 것을 알 수 있다.

핵심용어 : 딥 러닝, 파괴 모드, 적층 복합재, 전이 학습, DenseNet, GoogleNet