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IMAGE PROCESSING BASED DEEP LEARNING APPROACH FOR CLASSIFYING HYBRID FILLER RATIO IN GFRP

Huseyin KOSE[1]*, Ismail BAYAR[1]

[1]*Batman University, Faculty of Engineering and Architecture, Department of Mechanical Engineering, 72001, Batman, Türkiye*

Abstract: In this study, an image processing-based deep learning approach is developed to classify the filler ratios in glass fiber reinforced polymer composite with hybrid MgO-CuO nanoparticles in a non-contact and non-destructive manner, based solely on surface color and texture information. The originality of the study lies in its reliance on the direct learning of hybrid nanoparticle dopant ratios from optical surface properties, unlike image-based methods in the literature that mainly focus on damage detection, phase separation, or mechanical property estimation. In this context, eight different composite classes with different MgO and CuO weight ratios were produced and the samples were imaged at high resolution under homogeneous LED illumination at a fixed camera-sample distance. The obtained images were evaluated in a multi-class classification problem using the transfer learning-based EfficientNet-B0 architecture without any data enhancement. Model performance was analyzed with accuracy, sensitivity, recall, and F1-score metrics. Test results show that the proposed model achieved 97% overall accuracy and a macro-mean F1-score of 0.97; The study demonstrated that single-dopant and high-contrast hybrid systems were classified with high accuracy rate. Limited class overlap was observed in some hybrid classes with low CuO content, which is attributed to the optical similarity of the dopants. The findings reveal that deep learning approaches based on surface images offer a powerful, low-cost, and industrially viable alternative for dope ratio verification and rapid quality control applications in composite manufacturing processes.

Keywords: GFRP, Composite, Image processing, Deep learning, Hybrid filler classification

***Corresponding author:** Batman University, Faculty of Engineering and Architecture, Department of Mechanical Engineering, 72001, Batman, Türkiye
E mail: huseyin.kose@batman.edu.tr (H. KOSE)
Huseyin KOSE https://orcid.org/0000-0001-6500-975X
Ismail BAYAR https://orcid.org/0000-0002-4187-3911

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1. Introduction

Glass fiber reinforced polymer (GFRP) composites are widely used in many engineering applications due to their advantages of high strength, good chemical resistance, low density, and cost-effective production (Sathishkumar et al., 2014). They have a wide range of applications, particularly in the aerospace, automotive, construction, and energy sectors, including structural elements, insulation systems, and lightweight load-bearing components (Bobovich, 2019; Chrispin Laila et al., 2022; Karnati et al., 2020; Ma et al., 2016). However, the mechanical, thermal, and functional properties of glass fiber reinforced composites depend not only on the fiber-matrix interaction but also directly on the additives used and their distribution (Chrispin Laila et al., 2022).

In recent years, the use of micro and nano-sized particles reinforcements or functional additives to improve the performance of composite materials has become a significant research topic (Karnati et al., 2020). Nanoscale additives, thanks to their high surface areas, can provide effective bonding at the matrix-fiber interface, increasing mechanical strength, wear resistance, and thermal stability (Chrispin Laila et al., 2022). Metal oxide particles such as magnesium oxide (MgO) and copper oxide (CuO) are attracting attention in glass fiber reinforced composites due to their high hardness, thermal stability, and functional properties (Kose et al., 2024; Naveen et al., 2021). Besides the mechanical effects, MgO and CuO additives can lead to characteristic color and texture changes on the composite surface, creating distinctive optical properties depending on the type and ratio of the additive. This shows that these particles offer significant potential not only in terms of mechanical performance but also in terms of visual identification and traceability.

In industrial production processes, accurately controlling the type and ratio of powdered additives added to composite materials is critical for product quality and repeatability. However, traditional chemical analysis or microstructural characterization methods can be time-consuming, costly, and often damaging to the sample. Thus, artificial intelligence-based models constitute an important method in terms of both cost and process quality (Hart et al., 2021). Especially in data-rich areas such as material science, artificial intelligence-based models are being used very effectively (Li & Zheng, 2023). In this context, there is a growing need for a fast, contactless, and reliable quality control approach on the

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production line of the composites. Analyzing color and texture differences on the composite surface depending on the additive ratio using image processing and deep learning techniques offers an innovative solution to this need. Color-based additive ratio estimation provides significant advantages, especially in hybrid additive systems, for real-time monitoring of the production process and early detection of defective products. The use of image-based deep learning approaches in additive ratio classification in hybrid MgO-CuO reinforced glass fiber composites stands out as a research area with high potential from both academic and industrial perspectives.

Studies on image-based analysis and deep learning characterization of composite materials are increasing in the literature. Shim et al. (2024) aimed to predict the mechanical behavior of mechanically recycled carbon fiber reinforced composites using surface images; in this context, the modulus of elasticity, tensile strength, and stress-strain curves were successfully predicted with a CNN-based model, and it was reported that mechanical behavior prediction could be made with an error of less than 10%. Maghami et al. (2021) performed pixel-level segmentation using multi-illumination-based imaging and U-Net architecture for the automatic detection of damage around holes in CFRP materials and showed that the delamination factor could be calculated with an error of less than 5.4%. Badran et al. (2020) aimed to separate the fiber, matrix, and void phases from X-ray tomography images in SiC–SiC fiber-reinforced ceramic composites where no density difference exists; they demonstrated that up to 98% accuracy was achieved with deep learning-based segmentation, largely eliminating the need for manual segmentation. Similarly, Hu et al. (2023) aimed at intelligent interpretation of ultrasonic A-scan signals in composite materials; by combining 1D-CNN and an improved DiMP tracking algorithm, they enabled automatic detection and localization of internal damage, demonstrating that the proposed method outperformed traditional methods with 98.74% accuracy and a Kappa coefficient of 0.97. Fan et al. (2023) developed a CNN-based model for the rapid prediction of the mechanical behavior of composite laminates and achieved high prediction accuracy with lower computational cost compared to classical micromechanical models thanks to the automatic extraction of color, texture, and geometric features.

While current studies mainly focus on the detection of internal structural defects, microstructural phase segmentation, or mechanical property prediction, this study directly learns the optical differences arising from the type and ratio of additives in hybrid MgO-CuO reinforced glass fiber composites using deep learning. This study presents a unique approach that aims to classify nanoparticle additive ratios in composite materials contactless, solely based on surface color and texture information, unlike existing image-based deep learning applications in the literature. The proposed method demonstrates that additive ratios can be classified with high accuracy using only high-resolution surface images, without requiring any chemical analysis, X-ray tomography, or ultrasonic testing. Furthermore, the ability to consider hybrid additive systems together under multiple classes and to distinguish even visually overlapping compositions with low additive ratios stands out as a significant innovation in the literature. In this respect, the study demonstrates that image-based deep learning approaches can be integrated into production process monitoring and quality control applications in composite materials, offering a unique and applicable contribution from both academic and industrial perspectives.

2. Materials and Methods

2.1. Materials and Laminate Productions

In the present work, GFRP composites were fabricated using unidirectional E-glass woven fiber fabrics with a fiber diameter of 9 µm, a [(0°/90°)] orientation, and a surface weight of 200 g/m^2. The glass fiber fabrics were sourced from Dostkimya (Türkiye) and Hexcel (USA). CuO and MgO nanoparticles, used as reinforcing agents, were procured from Nanografi Nano Teknoloji (Türkiye), and their fundamental material properties are summarized in Table 1.

Table 1 Properties of the nanoparticles

Nano Particles	Purity (%)	Size (nm)	Surface Area (m^2/g)	Density (kg/m^3)
MgO	99.5	18	65	3600
CuO	99.9	38	20	6500

ARC-152 epoxy resin and W-152 hardener, both manufactured by ARCMARIN (Türkiye), were utilized as the matrix components in the composite fabrication. The ARC-152 epoxy exhibits adequate mechanical characteristics, including an elastic modulus of 950 MPa and a tensile strength of 43.35 MPa. Its elongation at break of 65% indicates a ductile behavior, while its relatively high density of 1100 kg/m^3 plays a critical role in influencing the overall composite performance. This epoxy system was selected due to its low viscosity, broad industrial applicability, and its capability to promote a more uniform dispersion of reinforcing additives within the matrix.

To achieve a uniform dispersion of MgO-CuO nanoparticles within the epoxy matrix and to minimize particle agglomeration, the nanoparticles were initially pre-dispersed in acetone using an ultrasonic bath. This was followed by a homogenization process involving both magnetic stirring and ultrasonic treatment after the addition of epoxy resin. After homogenization, the hardener was added, and hybrid nanoparticle-reinforced GFRP composites were fabricated in the form of 300x300 mm plates. The resulting composites had an average thickness of 1.3 ± 0.08 mm, a fiber weight fraction of approximately 52%, and varying MgO-CuO nanoparticle loadings ranging from 0.0% to 0.8% by weight, in 0.2% increments. A control sample containing no nanoparticles was also prepared. These samples were used as a reference sample to be able to make an accurate comparison. Produced samples with different reinforcement ratios and corresponding composite samples are presented in Table 2 with their weight ratio based on the corresponding class.

2.2. Data Acquisition Process and Dataset Preparation

During the data acquisition stage, a controlled imaging setup was established to ensure consistent and reproducible surface visualization of GFRP composite samples. As illustrated in Figure 1, the composite plates were positioned directly on a homogeneous LED light source, enabling uniform illumination and enhancing the visibility of surface color and texture variations induced by different nanofiller contents. A high-resolution camera was mounted perpendicular to the sample surface along the normal imaging axis, with the camera–sample distance fixed at h = 30 cm to eliminate perspective distortions and maintain constant imaging conditions for all samples. The schematic view of the data acquisition process is presented in Figure 1.

Table 2 Created classes based on produced composites samples

No	Sample	Class	MgO (wt. %)	CuO (wt. %)
1	0.4% CuO	C0.4	0	0.4
2	0.4% MgO	M0.4	0.4	0
3	0.8% CuO	C0.8	0	0.8
4	0.8% MgO	M0.8	0.8	0
5	0.4%MgO-0.4% CuO	M0.4C0.4	0.4	0.4
6	0.4% MgO-0.8% CuO	M0.4C0.8	0.4	0.8
7	0.8% MgO-0.4% CuO	M0.8C0.4	0.8	0.4
8	0.8% MgO-0.8% CuO	M0.8C0.8	0.8	0.8

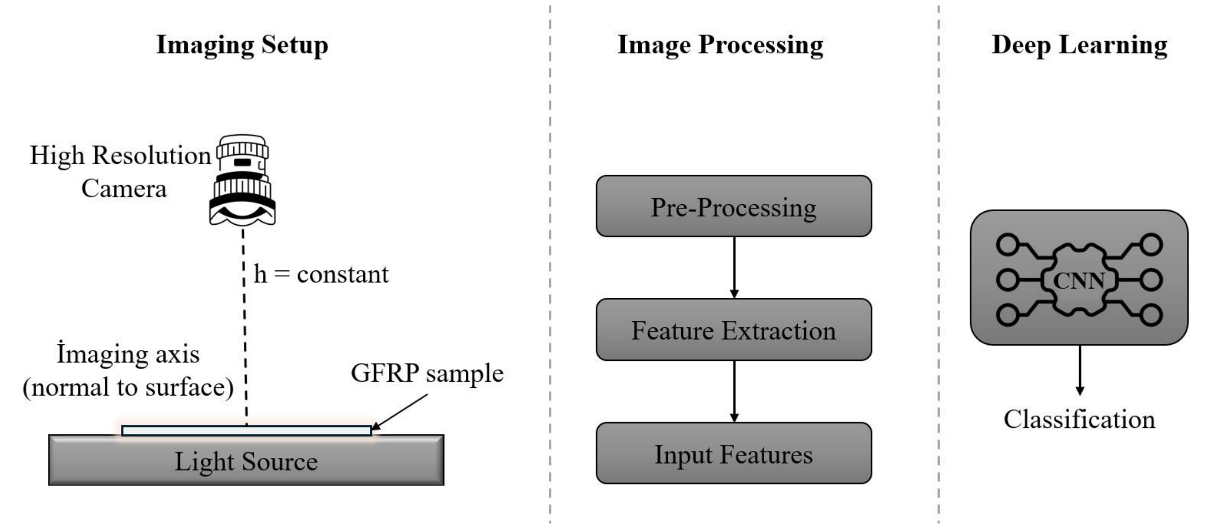

Figure 1. The schematic view of data acquisition process.

The image dataset used in this study was obtained from experimentally produced composite samples with different material types and reinforcement ratios. A total of eight different composite samples were produced, representing varying MgO–CuO nanoparticle ratios. MgO and CuO particles were hybridized and added to glass fiber reinforced composite samples, and the changes in the optical appearance (color/hue) of the samples were modeled using an image-based approach. Image data were organized under folders containing class information representing each mixing ratio. Folder names were defined to directly encode the MgO and CuO ratios in the sample as shown in class column in Table 2. Thus, target variables were automatically generated for each image with two outputs (multi-output). An average of 35 high-resolution images were obtained from each sample to represent their surface properties. Thus, the dataset was created with a sufficient number of images for each class. The resulting image dataset was randomly divided into 80% training and 20% testing datasets, maintaining the class distribution, for use in the model's training and performance evaluation processes. This approach ensured that the data used in the learning process and the data used in performance evaluation were kept independent of each other, and the model's generalization ability was reliably assessed. All recorded images were arranged in 224×224 pixels in size and evaluated in RGB format. Considering the input size requirements and computational efficiency of deep learning architectures, the images were rescaled and standardized to suit model input. Pixel values were converted to tensors, and then channel-based normalization was applied according to ImageNet statistics commonly used by transfer learning backbones. This process aims to more efficiently utilize the network's pretrained weights and improve training stability. Considering that color information plays a direct and decisive role in class differentiation, no color-based or geometric data augmentation methods were applied. This choice aims to prevent artificial variations from disrupting the class-label relationship and to avoid the model learning patterns that do not have a physical counterpart.

2.3. Deep Learning Model

Categorical class labels corresponding to different nanofiller compositions were numerically encoded to enable supervised learning. Feature extraction was then performed implicitly through the convolutional layers of the deep learning model, which automatically learned discriminative color and texture representations from the input images, and these learned features were finally utilized in the classification stage for reliable identification of composite nanofiller ratio classes. The dataset was divided into training and test subsets to reliably evaluate model performance. During the division process, a stratified division approach was adopted to ensure that each class was proportionally represented in both the training and test sets. This method ensured that all MgO-CuO ratio combinations were presented to the model in both the training and test phases, thus minimizing class imbalance and distribution biases. As mentioned earlier, the dataset was divided into 80% for training and 20% for testing. The classification model was constructed using a pre-trained Convolutional Neural Network (CNN) backbone on the ImageNet dataset. The EfficientNet-B0 architecture was chosen as the backbone because it offers a balanced structure between computational cost and representational power. The classification layer of the pre-trained network was removed, and a new fully connected output layer corresponding to the number of defined classes was added in its place. This approach enabled the effective use of the transfer learning strategy, achieving high performance even under limited data conditions. In model training, cross-entropy loss was used, suitable for multi-class classification problems. AdamW was chosen as the optimization algorithm. AdamW provides more stable and faster convergence thanks to its adaptive learning rate and weight decay mechanism. The model was trained for a specified number of epochs, and training loss and accuracy values were monitored at the end of each epoch. To reduce the risk of overfitting, multiple strategies were applied together. First, a transfer learning approach was used to prevent the model from learning low-level visual features from scratch; instead, a learning process based on previously learned general representation structures was implemented. Second, the AdamW algorithm was chosen during the optimization phase to activate the weight decay mechanism and control the overgrowth of model parameters. Furthermore, training performance was monitored not only through loss values but also through classification accuracy; thus, signs of overfitting were observed during the training process. Keeping the model complexity proportional to the dataset size also provided an indirect regularization effect. In addition, cross-validation principles were considered to examine the model's sensitivity to different data partitions, and maintaining the class distribution between partitions was adopted as a primary priority, given the limited size of the dataset. Thus, it was ensured that the obtained performance values were not specific to any particular data partition. The schematic view of the created model is shown in Figure 2.

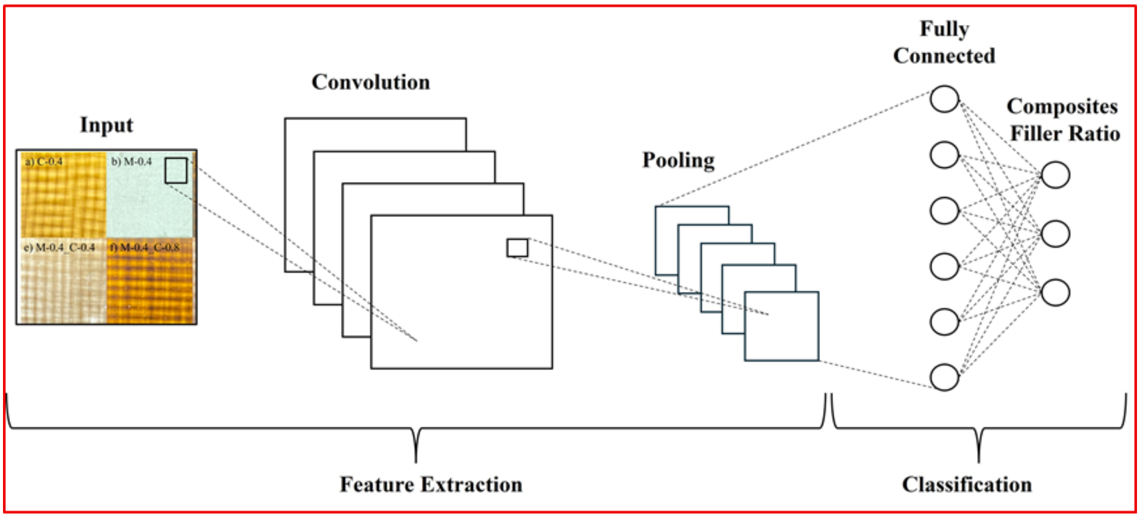

Figure 1. Schematic view of the deep learning model.

The model was trained over a total of 30 epochs, and preliminary tests showed that the model converged after approximately 30 epochs. Model performance was evaluated using multifaceted metrics on the test dataset. Overall classification performance was reported using the accuracy metric. A macro-averaged F1-score was also calculated to mitigate the effects of inter-class imbalances and to more clearly reveal class-based performance. Furthermore, precision, recall, and F1-score values were reported for each class; and a confusion matrix was created to analyze inter-class interference. The proposed method is designed for cases where the dopant ratios are defined at discrete levels, and these ratios create distinguishable color/texture changes on the sample surface. Therefore, the method focuses on reliably identifying specific mixture combinations rather than accurately predicting continuously changing ratios. However, limited class mixing can be observed in some low-contrast hybrid combinations, which is related to the similarity of the optical properties of the dopants.

3. Results and Discussions

The representative surface images of GFRP composite samples with different MgO and CuO dopant ratios are presented in Figure 3, obtained using the imaging setup developed and presented in methodology section. All images were obtained with a high-resolution camera positioned perpendicular to the sample surface under fixed camera-sample distance and homogeneous LED illumination conditions.

Examination of the images reveals significant differences in color tones, brightness levels, and surface texture between single-doped systems (a–d) and hybrid MgO-CuO doped systems (e–h). In particular, darker and more contrasting surface structures emerge with increasing CuO content, while lighter-colored and more homogeneous texture distribution predominates in MgO-dominant samples. In hybrid doped samples, it is noteworthy that color and texture properties change together depending on the interaction of both particles, and these changes create optical signatures sensitive to the doping ratio. These sample images demonstrate that the imaging method used can capture dopant-ratio-dependent surface properties with high repeatability and clarity; It also clearly demonstrates the physical basis of the distinctive visual information that the deep learning model uses in its classification process.

The representative surface images presented in Figure 3 highlight the distinct color and texture variations associated with different MgO and CuO nanofiller ratios, confirming the suitability of the acquired images for data-driven classification. These visually distinguishable patterns provide the fundamental input features exploited by the proposed deep learning model to learn discriminative representations among different composite classes. The training and validation loss and accuracy curves presented in Figure 4 demonstrate that the developed deep learning-based classification model converges quickly and stably. A significant decrease in both loss curves was observed in the first few epochs of the training process; after approximately 30 epochs, the loss value dropped below 0.2, exhibiting plateau behavior. The similarity of training and validation losses indicates that the model does not exhibit overfitting and has high generalization capability. This convergence behavior is consistent with previous image-based deep learning studies on composite materials, where stable loss reduction and parallel training–validation trends were reported for surface-based mechanical prediction and defect detection tasks (Badran et al., 2020; Maghami et al., 2021; Shim et al., 2024). Similar rapid convergence characteristics observed in these studies further support the robustness of transfer learning-based CNN architectures in extracting physically meaningful visual features from composite material systems.

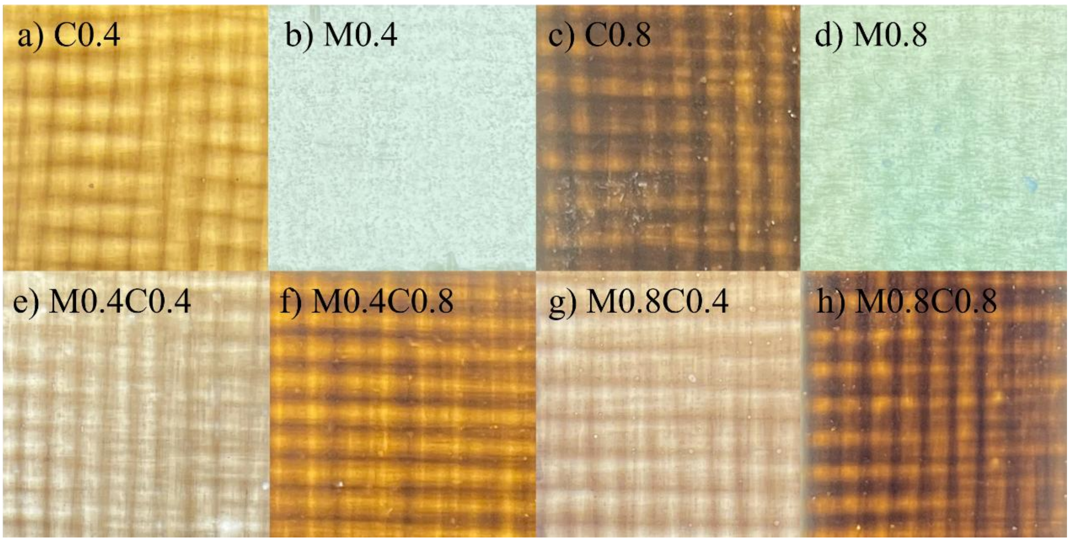

Figure 2. A representative example image of each class a) 0.4% CuO b) 0.4% MgO c) 0.8% CuO d) 0.8% MgO e) 0.4%MgO-0.4% CuO, f) 0.4% MgO-0.8% CuO, g) 0.8% MgO-0.4% CuO, h) 0.8% MgO-0.8% CuO.

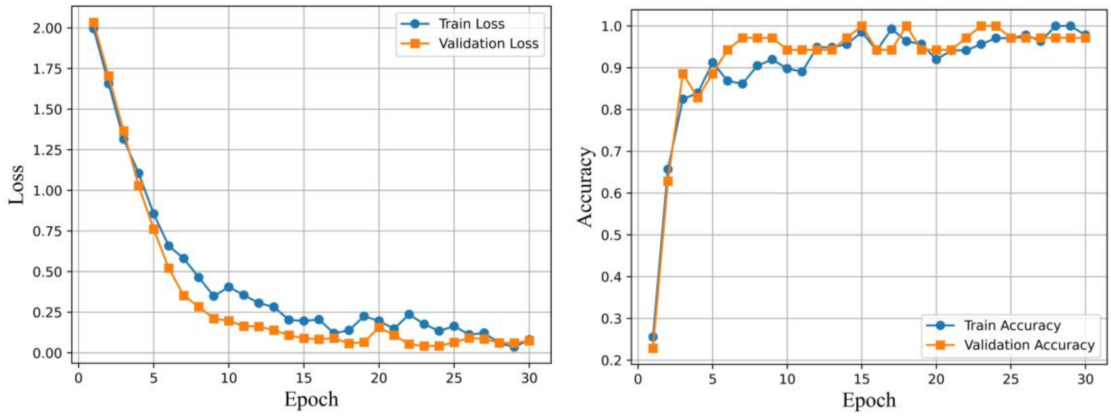

Figure 4. Evolution of training and validation loss and accuracy over epochs for the image-based deep learning classification model.

Examining the accuracy curves, it is seen that both training and validation accuracy exceed 90% within the first 5-6 epochs and then remain stable in the 95-100% range in subsequent epochs. The parallel progression of validation accuracy with training accuracy, in particular, shows that the model not only learns with a high accuracy rate in the training process but also provides high and consistent classification performance on the test/validation data. Similar high-accuracy and stable learning behavior have been reported in previous deep learning applications on composite materials, where transfer learning-based CNN architectures achieved classification or prediction accuracies above 95% while maintaining close alignment between training and validation curves (Hu et al., 2023; Maghami et al., 2021; Shim et al., 2024). These consistent findings indicate that convolutional feature extraction mechanisms are capable of effectively capturing discriminative visual signatures in composite systems, particularly when controlled imaging conditions and well-defined class structures are employed. The stabilization of the validation accuracy to approximately 97–100% and the loss of validation to less than 0.1 towards the end of the training process demonstrate that the proposed approach can produce reliable and reproducible results in the classification of hybrid MgO–CuO GFRP composites. This behavior, when evaluated together with the high-test accuracy and F1-score values obtained, confirms that the image-based deep learning approach can be used as an effective non-contact identification tool in this material system. Obtained precision, recall, F1-score and accuracy results are presented in Table 3.

Table 3 Obtained precision, recall, F1-score and accuracy

Metric	Precision	Recall	F1 score	Accuracy
Macro Avg	0.97	0.97	0.97	–
Weigh. Avg	0.98	0.97	0.97	–
Overall	–	–	–	0.97

Examining the classification results presented in Table 3, it is seen that the developed model exhibits generally high and balanced performance. Considering all classes, the overall accuracy obtained is 97%, and the macro mean F1 score is calculated as 0.97. These values indicate that the model has a consistent predictive ability not only for dominant classes but also for all combinations of contribution ratios. In addition to Table 3, class basis results were presented in Table 4.

It is observed that all systems containing only CuO or MgO (C0.4, C0.8, M0.4, M0.8) have precision, recall, and F1-score values of 1.00 when evaluated on a class basis. Similarly, the high-contrast hybrid combinations M0.4C0.8 and M0.8C0.8 classes were also classified flawlessly. These results show that the deep learning model can clearly distinguish the significant color and texture differences that occur as the type and ratio of additives increase. In contrast, limited mixing was observed in the M0.4C0.4 and M0.8C0.4 classes. The F1-score values for these classes were obtained as 0.89, respectively. The common feature of these classes is that the CuO ratio is low and constant (0.4%). This situation leads to the samples exhibiting optically very similar tonal and textural properties despite the variation in MgO content. Therefore, the limited misclassifications observed are related to the inherent visual overlap of the material system rather than a model deficiency. Similar behavior has been reported in previous composite material studies where deep learning models achieved near-perfect classification performance for high-contrast or distinctly separated classes, while minor confusion occurred in classes with overlapping visual or microstructural signatures (Fan et al., 2023). In particular, it has been emphasized that when inter-class optical contrast decreases, performance degradation is primarily associated with intrinsic material similarity rather than limitations of the convolutional architecture itself. The confusion matrix presented in Figure 5 demonstrates that the developed deep learning-based classification model can distinguish hybrid MgO-CuO doped glass fiber composites with high accuracy and consistency. The fact that the majority of diagonal elements in the matrix have a value of 1.00 indicates that all single-doped systems (C0.4, C0.8, M0.4, M0.8) and high-contrast hybrid combinations (M0.4C0.8 and M0.8C0.8) are correctly classified, and the recall values for these classes are near perfect. This shows that color and texture differences, depending on the type and ratio of doping, provide a strong and distinctive visual signal for the image-based deep learning model.

In contrast, limited interference was observed only in the M0.4C0.4 class; While 80% of the samples belonging to this class were correctly classified, minor errors were observed in 20% of them in M0.8C0.4 class. These errors are related to the fact that both classes exhibit optically very similar properties in terms of color tone and surface texture due to their low and constant CuO content (0.4%). However, the fact that the errors occur only in this limited composition region and in a unidirectional manner indicates that the model correctly learned the general classification limits and only experienced uncertainty in hybrid systems where optical overlap is high. Overall, the confusion matrix analysis confirms that the proposed method has strong potential for contactless and reliable classification of hybrid MgO-CuO-reinforced glass fiber composites.

Table 4 Obtained precision, recall and F1-score by class

Class	Precision	Recall	F1-score
C0.4	1.00	1.00	1.00
C0.8	1.00	1.00	1.00
M0.4	1.00	1.00	1.00
M0.8	1.00	1.00	1.00
M0.4C0.4	1.00	0.80	0.89
M0.4C0.8	1.00	1.00	1.00
M0.8C0.4	0.80	1.00	0.89
M0.8C0.8	1.00	1.00	1.00

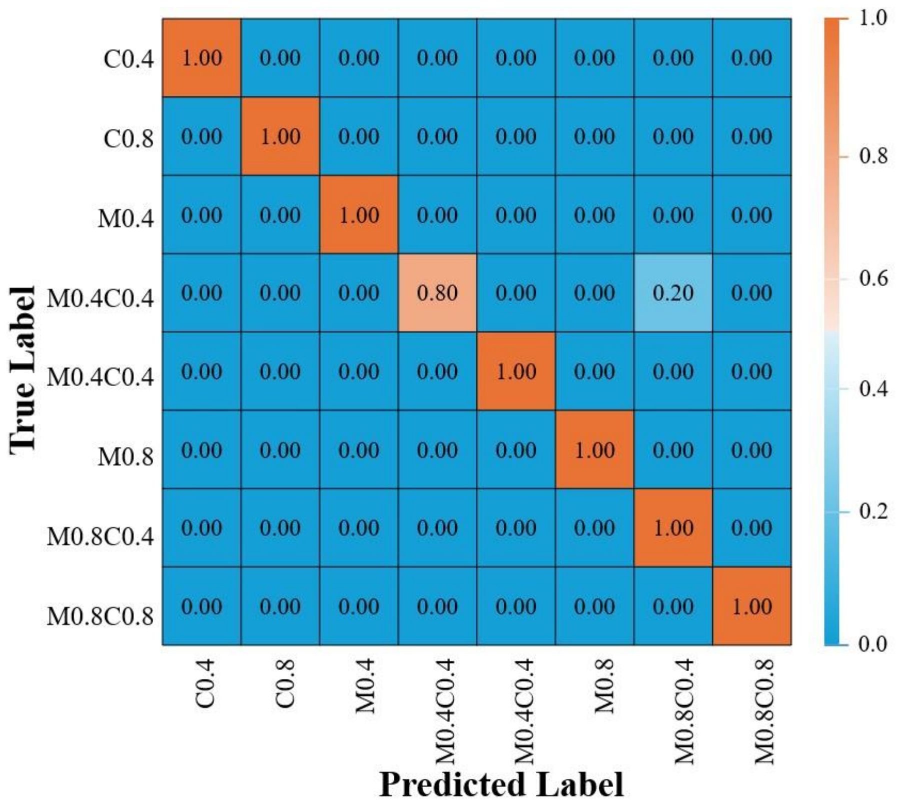

Figure 3 Confusion matrix of the deep learning model

4. Conclusion

This study addresses the classification of dopant ratios in hybrid MgO-CuO nanoparticle-reinforced glass fiber composites using deep learning and image processing based solely on surface color and texture information. The feasibility of a contactless and rapid identification approach is investigated using a dataset created for eight distinct composition classes with different MgO and CuO ratios.

In the proposed method, a pre-trained EfficientNet-B0 architecture is used with a transfer learning approach, and an eight-class classification problem is defined. The model is trained with data enhancement techniques and a cross-entropy loss function. A balanced and stable convergence is achieved in the training and validation processes. The main originality of this study is that hybrid nanoparticles dopant ratios in composite materials can be classified solely through surface images, without requiring any chemical or destructive testing. Unlike studies in the existing literature, which mainly focus on damage detection or mechanical property prediction, the aim is to directly learn optical differences dependent on dopant ratio.

The obtained results demonstrate that the proposed model offers a high classification performance. A 97% overall accuracy and a macro F1 score of 0.97 were obtained on the test data; single-doped and high-contrast hybrid systems were classified without error. Interference observed in a limited number of hybrid combinations with low CuO ratios is due to optical overlap.

These findings reveal that the developed approach has strong potential for rapid quality control and additive validation applications in composite manufacturing processes. However, the limitation of the method to discrete dopant ratios and its evaluation under controlled illumination conditions are the main limitations of the study. Future studies aim to estimate continuous dopant ratios, investigate the effect of different imaging conditions, and integrate the method into real-time industrial systems.

Author Contributions

The percentages of the authors' contributions are presented below. All authors reviewed and approved the final version of the manuscript.

	H.K.	İ.B.
C	50	50
D	50	50
S	50	50
DCP	35	65
DAI	65	35
L	50	50
W	50	50
CR	50	50
SR	65	35
PM	50	50

C= concept, D= design, S= supervision, DCP= data collection and/or processing, DAI= data analysis and/or interpretation, L= literature search, W= writing, CR= critical review, SR= submission and revision, PM= project management.

Conflict of Interest

The authors declared that there is no conflict of interest.

Ethical Consideration

Ethics committee approval was not required for this study because of there was no study on animals or humans.

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