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Automated Microstructure Classification with Class-Specific Segmentation for Titanium Based Composite Materials

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Abstract

In engineering, characterisation of microstructure is required to determine and forecast behaviour of titanium alloys. Our proposal in this work has been a deep-learning-based framework in the automatic classification and segmentation of Titanium Based Composite Material. The framework then uses EfficientNetB0 backbone, where we have chosen the backbone to scale the performance of classification and the computational efficiency with the assistance of the transfer learning and the compound scaling. In a bid to enhance the interpretability, we use class-specific segmentation once we have done the classification, which means that the segmentation policy can be adjusted to the morphological features of each predicted class. This causes the identification of duplex, lamellar and martensitic microstructures. The network is trained on the basis of the Adam optimiser and categorical cross-entropy loss, and a stratified approach to data-splitting is used to overcome the imbalance between classes. The model achieved a mean classification accuracy of 96.73% ± *0.67%, with a best observed accuracy of 97.55% and good macro F1-score and AUC results were achieved through experimental assessment on the test set, and these results demonstrate good generalisation across all microstructural classes. In the course of the experimentation, we noted that the proposed framework may facilitate the effective and interpretable microstructural analysis, which is why it may be applied to metallurgical research and quality control in industries.*

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INTRODUCTION

Understanding the mechanical and physical behaviour of metallic alloys is essential for their reliable use in engineering applications. Titanium Based Composite Material, in particular, is widely used in aerospace, biomedical, and automotive components because of its favourable strength-to-weight ratio, corrosion resistance, and fatigue performance. Requires microstructural characterization [1–2]. For quality control, process optimization, and accurate in-service performance prediction, microstructural phases like duplex, lamellar, and martensitic structures must be accurately identified [3], [5], [6].

Manual inspection of optical and scanning electron microscopy pictures is the basis for conventional micro structure evaluation. This method is laborious, subjective, and largely dependent on expert interpretation [4],[7],[8], [9]. Reproducibility is further hampered by subtle morphological differences, imaging artifacts, and variability brought on by heat-treatment conditions [10]-[14].

By enabling models to learn discriminative feature representations directly from picture data, recent developments in computer vision and deep learning have made automated microstructural analysis possible [15]-[25]. In a variety of metallic systems, convolutional neural networks (CNNs) have proven to perform well in phase recognition, grain morphology characterisation, and defect detection [8]–[10]. However, when trained on relatively small metallurgical datasets, many deep learning architectures have limited generalization and significant computational costs [11]-[13].

In order to overcome these constraints, this work suggestsan EfficientNetB0-based framework for automated Titanium Based Composite Materialmicrostructure segmentation and classification that achieve sexcellent predicted accuracy while preserving computing economy appropriate for practical metallurgical applications.

METHODOLOGY

Dataset

We worked with a public dataset of 1,225 optical micrographs of Titanium Based Composite Material microstructures. The dataset contains 688 duplex, 351 lamellar, and 186 martensitic images. Each image was manually labelled based on visible phase morphology and grain characteristics to ensure reliable ground-truth annotations. The images exhibit natural variations in grain size, phase distribution, and image quality, reflecting realistic experimental conditions. This variability helps the model learn structural patterns that are meaningful for practical metallurgical analysis. To ensure fair evaluation, the dataset was divided using stratified sampling into 60% (735 images) for training and 20% each (245 images) for validation and testing, while preserving class proportions across all subsets. Because the dataset is imbalanced, class-weighted loss was applied during training to promote balanced learning across the three microstructure types.

Data Preprocessing

We started by resizing all the microstructure images to 224 by 224 pixels so they'd fit EfficientNetB0's input. Before that, we used a light Gaussian blur on the grayscale images to smooth out noise. Then, we normalized the pixel values between 0 and 1—this keeps training more stable. Since EfficientNetB0 expects three-channel images, we took each grayscale micrograph and copied its intensity channel into all three channels. That way, the details stay the same. For data augmentation, we only transformed the training set. We threw in random rotations (up to 20 degrees), small width and height shifts (0.08), a bit of shear (0.05), zoom (0.08), and some horizontal flips. These tweaks help the model handle images from different angles and sizes, which cuts down on overfitting. We left the validation and test images untouched, so our performance results stay real and fair.

Data Splitting

It is divided into a dataset according to a stratified strategy where each subset contains all the microstructure classes equally. Approximately 60 percent of the images are utilized in training the model. It has a validation set, which includes 20 percent of the data and is needed to keep track of training performance and adjust model parameters. The rest 20 percent of data is used in testing. Class imbalance can mess with model learning. so we applied class-weighted loss during training. The weights were 0.59 for duplex, 1.16 for lamellar, and 2.19 for martensitic. For statistical reliability, experiments were conducted using three different random seeds (42, 52, and 62), ensuring consistent data splitting and evaluation across independent runs. This approach helps avoid data leakage and gives a solid, honest look at how well the model handles new, unseen data.

Proposed Architecture

The proposed framework applies EfficientNetB0, which is a small convolutional neural network trained on ImageNet dataset, to examine the Titanium Based Composite Material microstructure images. The reason we selected EfficientNetB0 is that it offers an appropriate trade-off between accuracy of classification and the computational cost with its strategy of scaling networks by running a compound scaling strategy which simultaneously scales the network depth, width, and input resolution. This is what causes the model to fit microstructural datasets of moderately high size with complex visual features. EfficientNetB0 uses depthwise separable convolutions and inverted residual blocks. It makes use of less trainable parameters. Processes maintain good ability of feature learning. The pretrained network can be treated as a powerful feature extractor and important microstructural features like the morphology of grains, phase boundaries, and variations in texture can be identified. These characteristics can be used to differentiate between duplex, lamellar, and martensitic microstructures.

Microstructure Classification

For the classification part, we swapped out the original ImageNet output layer for a new head tailored to our task. The model first runs the feature maps through a Global Average Pooling (GAP) layer, then passes them to a fully connected layer with ReLU activation, and drops some nodes (dropout rate 0.5) to help avoid overfitting. At the end, a softmax layer spits out probability scores for the three classes. Training uses transfer learning in two steps.

First, we freeze the pretrained backbone and train the new classification head for 10 epochs, using the Adam optimizer (learning rate 1e-4, batch size 16). Next, we unfreeze the last 40 layers of the backbone and fine-tune everything for another 10 epochs at a lower learning rate (1e-5). To handle class imbalance, we use categorical cross-entropy loss with class weights (0.59 for duplex, 1.16 for lamellar, 2.19 for martensitic). All experiments were performed using three independent random seeds (42, 52, and 62) to assess reproducibility and performance stability.

Class-Specific Segmentation

Once the classification is completed, the foreseen microstructure class is utilized as a guide towards the segmentation. Different segmentation methods are used to each type of microstructure, as there are different visual characteristics attributed to each type of microstructure. Contrast enhancement, edge detection, and watershed segmentation are used in identifying the boundaries of the grains and phases in duplex microstructures. Directional gradients are used to highlight lamella patterns within lamellar microstructures through the extraction of lamella patterns. The microstructures of martensitic are subjected to intensity-based thresholding and morphological operations to bring out fine needle-like structures. This is the stage of segmentation that is used as post-processing and does not need further model training. The suggested structure enhances the interpretability of the results by the combination of the EfficientNetB0-based classification and class-specific segmentation to aid meaningful metallurgical analysis.

As shown in Fig. 1, the architecture is modular, withEfficientNetB0 serving as the main feature extractor and alightweight classification head handling microstructure prediction. The clear separation between feature extraction, classification, and segmentation maintains both accuracy and interpretability, enabling reliable identification of duplex, lamellar,and martensitic microstructures.

PERFORMANCE EVALUATION AND RESULT ANALYSIS

With an overall classification accuracy of 96.73% ± 0.67% (best: 97.55%), the proposed EfficientNetB0-based framework demonstrates strong and balanced performance in the classification of Titanium Based Composite Material, described in table 1. Compared with conventional two-stage pipelines and widely used CNN architectures such as VGG, ResNet, and DenseNet, the proposed approach achieves higher accuracy while significantly reducing computational complexity. Although deeper networks are capable of learning highly discriminative features, their large parameter counts increase training cost and susceptibility to overfitting when applied to limited microstructural datasets. EfficientNetB0 addresses these challenges through compound scaling, enabling an optimal balance between model expressiveness and computational efficiency.

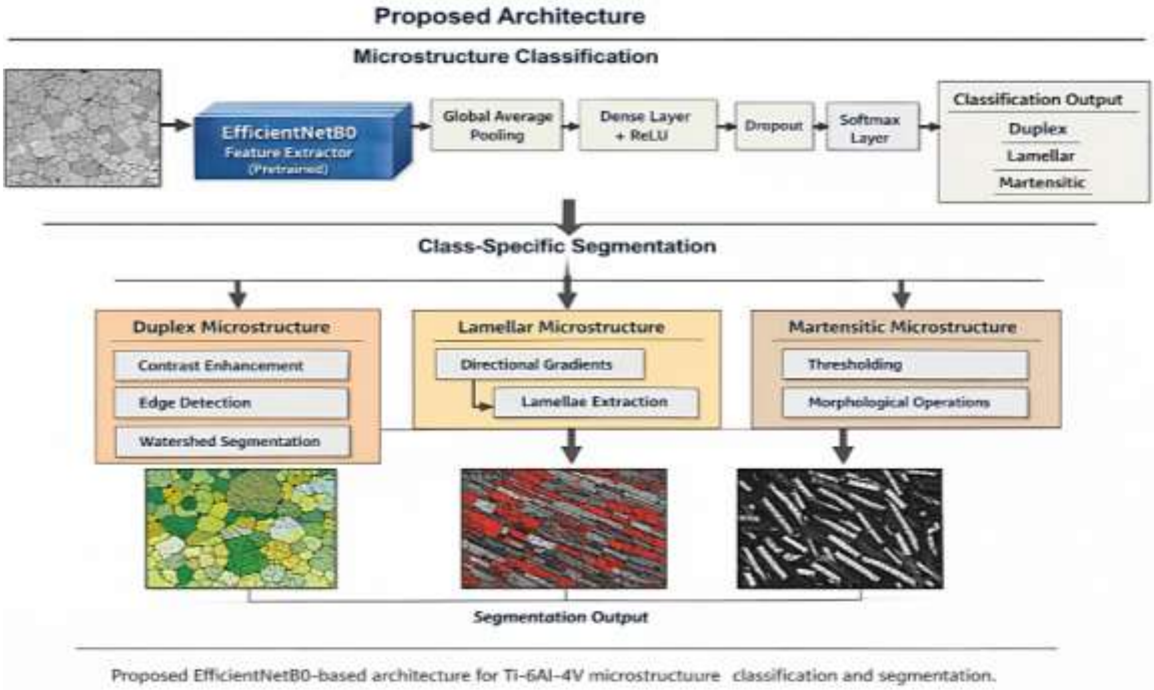

Figure 1. Proposed EfficientNetB0-based architecture for Titanium Based Composite Material microstructure classification and segmentation.

Table 1. Comprehensive Performance Evaluation of Literature Models and Present Work

Model / Approach	**Typical Performance**	**Characteristics / Notes**
Two-Stage Pipelines [8], [11]	78–85%	Classification followed by class-specific segmentation; suitable for morphology-dependent workflows.
ResNet / VGG / DenseNet [13], [14]	85–88%	Strong baseline models; deeper architectures improve accuracy but increase computational cost and overfitting risk.
EfficientNet (General) [15]	88–93%	Excellent accuracy–efficiency trade-off; effective on limited microstructure datasets due to compound scaling.
U-Net Variants [17]	High segmentation quality	Capture spatial hierarchies; attention and dilated variants enhance structural boundary detection.
Hybrid DL + Watershed [16], [18]	Robust segmentation	Combines CNN predictions with morphological operations; yields interpretable and physically meaningful masks.
EfficientNetB0 [15], [19] (Present Work)	96.73% ± 0.67% (best: 97.55%) macro AUC = 0.9981 (multi-run evaluation over 3 seeds)	Balanced performance with macro F1=0.9650 and AUC=0.9981; computationally efficient architecture

To assess the stability of the proposed framework, we conducted three independent experiments using different random seeds (42, 52, and 62), repeating the full training and evaluation process each time to examine sensitivity to initialization and data shuffling. The resulting test accuracies were 97.55%, 95.92%, and 96.73%, yielding a mean accuracy of 96.73% with a standard deviation of ±0.67%. The difference between the highest and lowest run was only 1.63 percentage points, indicating consistent performance rather than dependence on a favourable split. Beyond overall accuracy, class-wise precision, recall, and F1-scores were evaluated, with a macro F1-score of 0.965 and a weighted F1-score of 0.967, demonstrating balanced performance across duplex, lamellar, and martensitic microstructures despite dataset imbalance. The macro-average AUC reached 0.9981, reflecting excellent class separability, as further supported by ROC analysis. The confusion matrix showed only 8 misclassifications out of 245 test samples (3.27% error rate), with most errors occurring between duplex and lamellar classes, which are occasionally morphologically similar, while martensitic samples were rarely confused.

Multi-Run Convergence and Statistical Stability Analysis Based on Accuracy and Loss Curves

Look at the training and validation curves across these three experiments, described in fig 2 and we'll see the same story every time. At first—let's say, during the first 10 epochs—training accuracy climbs from about 0.35–0.55 all the way up to 0.92–0.93. Training loss drops at a similar pace, starting above 1.0 and settling near 0.30–0.35. That's a clear sign the model's optimizing well, especially with the backbone frozen. Then, at epoch 11, things get interesting. The last 40 layers unfreeze for fine-tuning, resulting in a temporary fluctuation in performance metrics: a small uptick in training loss, and accuracy dips for a bit. Not surprising—suddenly, a lot more parameters are updating. But the model handles it. Everything stabilizes fast, and those accuracy numbers keep improving. It's controlled fine-tuning, not chaos.

Validation accuracy mirrors this process. It levels off above 0.95 and usually ends up around 0.97–0.98 by the last few epochs. Validation loss keeps shrinking, and you don't see any runaway overfitting. In the end, test accuracies land at 97.55%, 95.92%, and 96.73%—averaging 96.73% with a tight standard deviation of just ±0.67%. That consistency, both in the numbers and the learning curves, shows the model's performance is reproducible and reliable for automated Titanium Based Composite Material microstructure classification

Confusion Matrix & ROC Curve

The receiver operating characteristic (ROC) curves for the suggested EfficientNetB0-based Titanium Based Composite Material microstructure classification framework are displayed in Figure 3. Strong class separability is demonstrated by the ROC curves, which consistently show high true positive rates at low false positive rates across all three microstructural classes. The robustness of the learnt feature representations is confirmed by the large area under the curve (AUC = 0.9981), which also shows that the model can efficiently generalize in spite of minute morphological alterations.

The confusion matrix, shown in fig 4, breaks down performance across 245 test samples. Out of those, 237 are classified correctly, giving an overall accuracy of 96.73%. Only 8 samples are misclassified. The matrix shows a strong diagonal, which tells us the model is consistent across all three categories. For duplex, there are 132 correct predictions and six errors, most of which get mixed up with lamellar. Lamellar fares even better: 69 correct, just one mistake. Martensitic stands out with 36 correct and only one error. Few off-diagonal entries mean the model rarely confuses one class for another. Pair that with a macro F1-score of about 0.965, and the evidence is clear—the model handles classification tasks well and generalizes strongly for automated metallurgical microstructure analysis, described in table 2.

Class-Specific Segmentation Analysis

The obtained results of segmentation prove the effectiveness of the proposed classification-based framework. To predict the input microstructure image, the EfficientNetB0 model is used to first determine whether the input image is in the duplex, lamellar, or martensitic category. This forecasted label is then applied to choose the right segmentation method. With such a class-sensitive strategy, a segmentation procedure works on the most significant attributes of any type of microstructure.

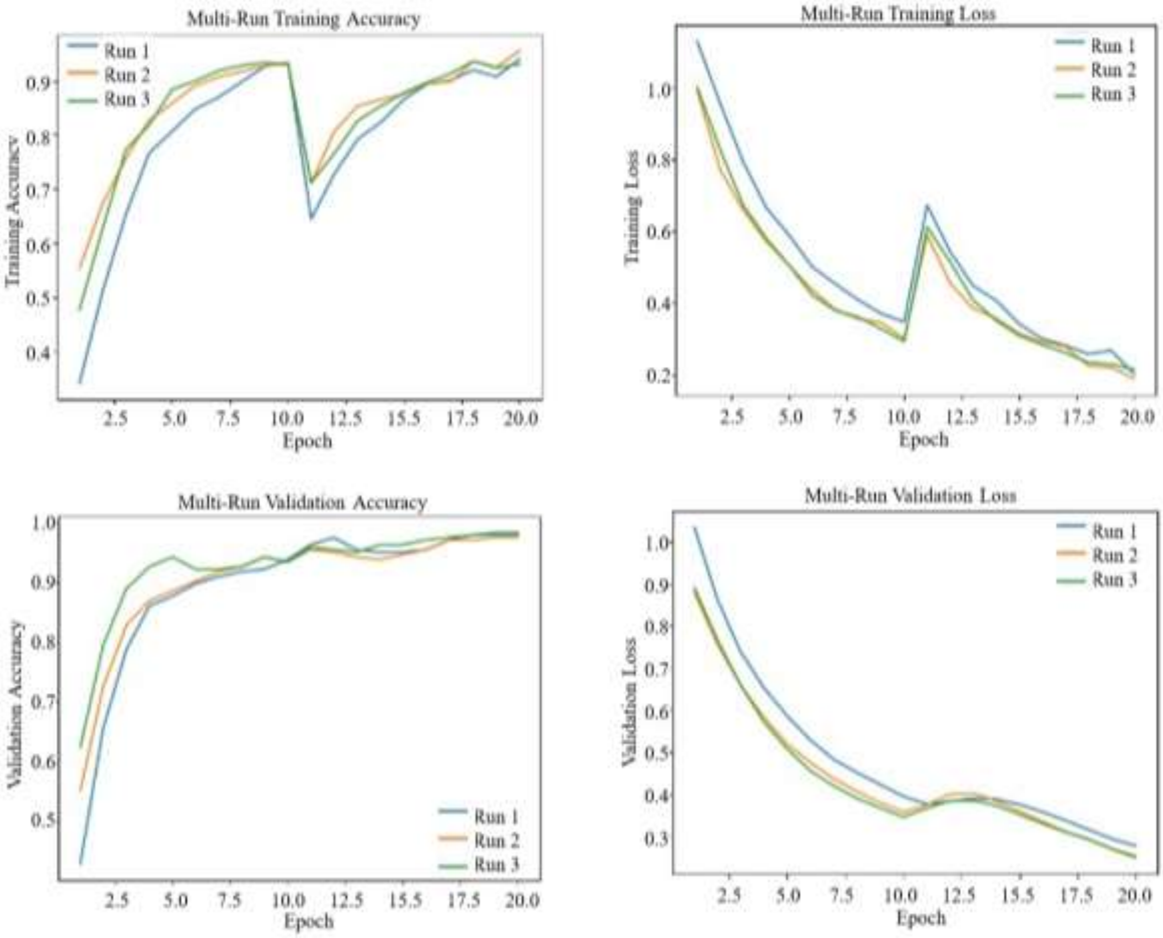

Figure 2. Multi-Run Training and validation accuracy and loss curves for the proposed Architecture

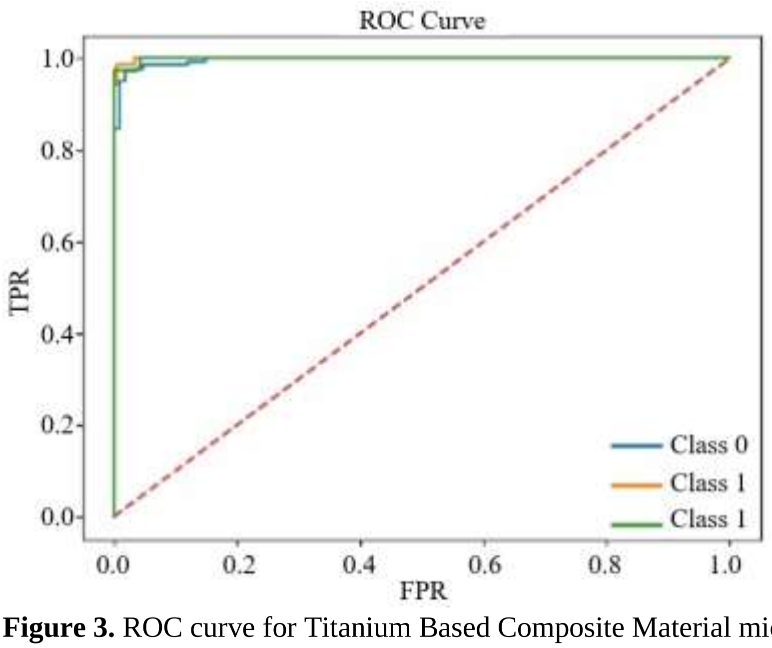

Figure 3. ROC curve for Titanium Based Composite Material microstructure.

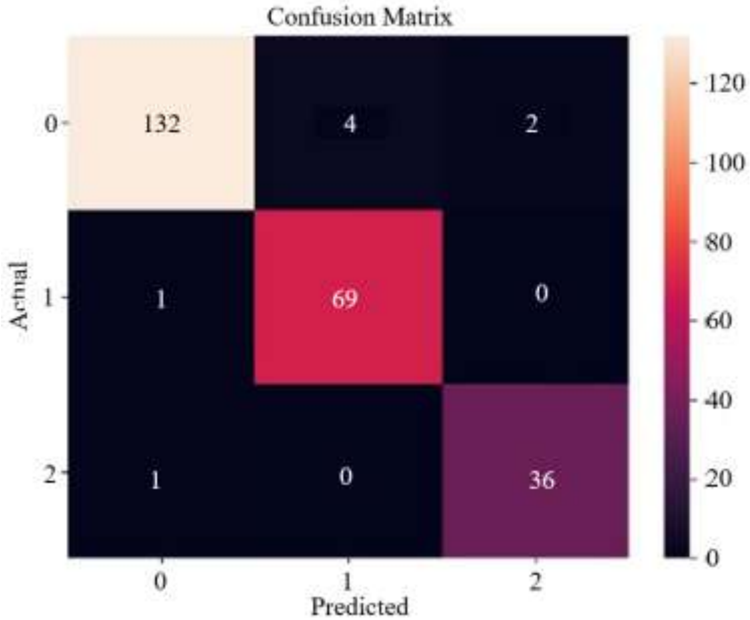

Figure 4. Confusion matrix

Table 2. Class-wise Performance on Test Set Calculated Using Confusion Matrix

Class	Precision	Recall	F1-score	Support
Duplex	0.985	0.957	0.970	138
Lamellar	0.945	0.986	0.964	70
Martensitic	0.947	0.973	0.959	37
Macro Avg	0.959	0.972	0.965	245
Weighted Avg	0.967	0.967	0.967	245

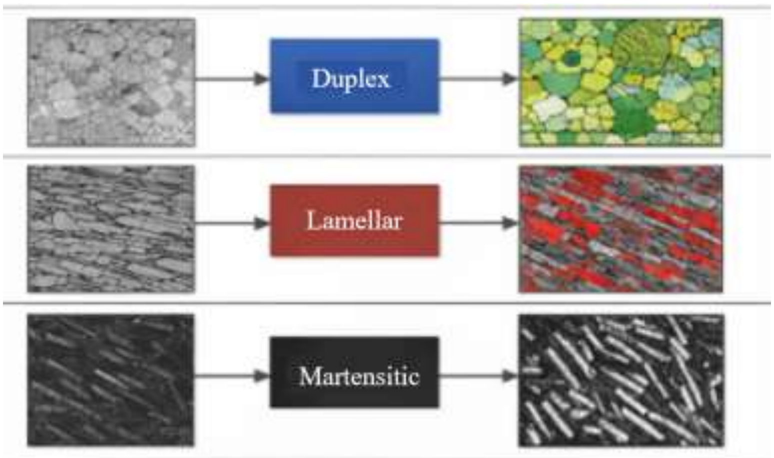

Figure 5. Segmentation

In the case of duplex microstructures, explained in fig 5, grain and phase boundaries are well brought out in the segmentation results. Watershed-based processing assists in the separation of neighbouring grains with minimal overlap. In the lamellar microstructures, the broken up images have distinct layered images and directional gradients can be used to determine the lamella orientation and continuity accurately by the use of directional gradients. In the case of martensitic microstructures, fine needle-like structures are strongly highlighted after simple intensity-based thresholding and morphological processing.

In general, the analysed segmented products are in agreement with the established metallurgical properties of Titanium Based Composite Material. The findings are full of less noise and significant structural boundaries. All the three classes show consistent performance in segmentation, and the assessment of the results on a visual scale shows that the labels of the predicted classes are in agreement with the resulting segmented structures. The two outputs, classification and segmentation, enhance interpretability and facilitate the automatic and reliable microstructure analysis.

Ablation Study: Class-Specific vs Generic Segmentation

To see how well the class-specific segmentation strategy works, we compared it to a generic baseline. For the baseline, we used the same segmentation method for every microstructure class, ignoring their predicted labels. This generic approach found some structural boundaries, but it didn't reliably capture the unique shapes of duplex, lamellar, or martensitic structures, described in table 3.

The class-aware framework takes a different path. It adapts the segmentation process based on the predicted phase. Duplex samples show grains that are more clearly separated. Lamellar structures come through with sharper layer definition and more consistent orientation. Martensitic images keep their fine, needle-like patterns with less distortion. This side-by-side comparison makes it clear: when we let the segmentation process respond to the classification output, the results aren't just easier to interpret. They actually match the true physical features of each microstructure type more closely.

Table 3. Comparison Between Generic and Class-Specific Segmentation Approaches

Microstructure Type	Evaluation Aspect	Generic Segmentation	Proposed Class-Specific Segmentation
Duplex	Grain Boundary Separation	Partial separation; some merged grains	Clear grain separation using watershed transformation
Duplex	Boundary Continuity	Irregular and fragmented edges	Continuous and well-defined boundaries
Lamellar	Layer Extraction	Inconsistent detection of parallel layers	Directional filtering preserves lamellar orientation
Lamellar	Structural Clarity	Moderate contrast with overlapping regions	Distinct layered morphology with improved contrast
Martensitic	Needle Feature Detection	Loss of fine acicular details	Fine needle-like structures preserved
Martensitic	Noise Suppression	Background noise present	Reduced noise after morphological refinement
All Classes	Morphology Consistency	Same processing applied to all images	Processing is adapted to the predicted phase
All Classes	Interpretability	Limited structural differentiation	Phase-aware and physically meaningful output
All Classes	Phase Alignment	Not conditioned on classification output	Directly conditioned on predicted microstructure

CONCLUSION

Our labour is based on a foundation of EfficientNetB0 and introduces a successful deep learning system to classify and segment Titanium Based Composite Material microstructures. This model is characterised by high classification accuracy of 96.73%±0.67%(best:97.55%) and macro F1 and macro AUC, which we observed to be reliable in discrimination between duplex, lamellar, and martensitic microstructures using transfer learning and compound scaling. Although we preserve the computational capabilities that are appropriate to achieve the practical purposes of metallurgy, we deal with issues concerning minor morphological differences, small data quantities, and imbalance between classes that we see in experiments. The key benefit of the suggested approach is that it has a modular architecture, which we intended to couple microstructure classification with class-specific segmentation pipelines. The design makes it easier for the materials scientists and engineers to interpret materials because it allows the accurate prediction of classes as well as the extraction of physically meaningful descriptors, including phase boundaries and texture features. In comparison with the workflow of other conventional two-stage and more complex CNN models, we can note that the network presented by EfficientNetB0 provides a better balance between accuracy, robustness, and inference time.

Further development of the generalisation should be done by increasing the number of alloy chemistries, heat-treatment conditions, and imaging modalities in the datasets in the future. Another multi-scale and multi-modal learning approach that we will explore includes processing parameters with microstructural images. Further research will be done to integrate into digital production pipelines and operate in real time in industrial inspection settings. During such developments, we will put ethical considerations as a priority to ensure that data integrity, transparency, and responsible deployment of AI-based metallurgical analysis systems are put into consideration. To sum up, our findings demonstrate the utility of deep learning in automated characterisation of microstructure. The suggested framework offers an information-supported, scalable, and interpretable framework to aid in data-driven decision-making in the area of material design, quality inspection, and process optimisation due to its combination of accuracy, interpretability, and computational efficiency.

LIMITATIONS

Although the proposed framework demonstrates strong classification and segmentation performance, certain practical limitations should be acknowledged. While EfficientNetB0 is computationally efficient compared to heavier convolutional architectures, real-time deployment in industrial inspection environments remains dependent on the availability of sufficient computational resources. In hardware-constrained settings, inference speed may become a limiting factor, particularly in high-throughput applications. Furthermore, the framework has been developed and validated specifically for Titanium Based Composite Material. Variations in alloy systems, phase morphology, imaging conditions, or material composition may require retraining or adaptation to achieve comparable performance levels.

AUTHORS CONTRIBUTION:

The first author and the second author contributed equally to this work and share first authorship.

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