SEM Image Classification Using CNN Architectures

G. Türkmen, Ö. Tekin, K. Kurtuluş, Y. Y. Yurtseven, M. Baran

Abstract**—**A scanning electron microscope (SEM) is a type of electron microscope mainly used in nanoscience and nanotechnology areas. Automatic image recognition and classification are among the general areas of application concerning SEM. In line with these usages, the present paper proposes a deep learning algorithm that classifies SEM images into nine categories by means of an online application to simplify the process. The NFFA-EUROPE - 100% SEM data set, containing approximately 21,000 images, was used to train and test the algorithm at 80% and 20%, respectively. Validation was carried out using a separate data set obtained from the Middle East Technical University (METU) in Turkey. To increase the accuracy in the results, the Inception ResNet-V2 model was used in view of the Fine-Tuning approach. By using a confusion matrix, it was observed that the coated-surface category has a negative effect on the accuracy of the results since it contains other categories in the data set, thereby confusing the model when detecting category-specific patterns. For this reason, the coated-surface category was removed from the train data set, hence increasing accuracy by up to 96.5%.

Keywords**—**Convolutional Neural Networks, deep learning, image classification, scanning electron microscope.

I. Introduction

WITH the advancement of technology, Artificial Intelligence (AI) has been widely used in medical imaging and nanotechnology areas. AI innovations have inspired many articles and studies, including image classification and image recognition techniques, e.g. [1]. Nanotechnology, in particular, is one of those fields using such deep learning techniques as an effective tool since many images in this field are a typical product of Scanning Electron Microscopy (SEM) [1]. In detail, the images are obtained by an electron beam of high energy projected onto the sample surface; hence, the term 'scanning electron microscope' [2]. When dealing with big data, manual observation becomes a handicap to examine information, to predict data behavior, and to solve complex relationships. Besides, long-term management of information on this scale becomes another hurdle. Therefore, it is crucial to create applications dependent on deep-learning procedures to overcome each of these difficulties. To this end, automatic image recognition of SEM images can be beneficial for nanoscience researchers, mainly because it eliminates the need for manual classification and provides a searchable database of related images categorized in a way that facilitates access [3].

This article uses the NFFA-EUROPE - 100% SEM data set containing 21,169 images classified into 10 categories to train and test the algorithm and to improve its accuracy results. After reviewing relevant studies in the literature, the decision was made to commence the process using the Inception-V3 model followed by the application of transfer learning methods. Also, in the scope of this study, a simple web application is provided for carrying out the classification.

II. Related Work

In the study of Modarres et al., a data set of 18,577 SEM images was created by classifying the images manually into 10 categories for training, and a second data set consisting of 1068 SEM images was created for testing. The training set was used to re-train the SEM data set and to compare the Inception-v3, Inception-v4, and ResNet models, followed by feature extraction. Inception-v3 had the best results in accuracy and performance, achieving around 90% [1].

In the project carried out by De Nobili, transfer learning was widely studied using the ImageNet pre-trained checkpoints of Inception-v3, Inception-v4, Inception ResNet-v2, and DenseNet-121. Similar to the case of training from scratch, Inception-v3 and, in particular, DenseNet-121 demonstrated better performances in terms of accuracy and timing for the project. Both Inception-v3 and DenseNet-121 were fine-tuned up to 214 epochs, but DenseNet-121 took significantly less time to reach a stable higher accuracy of 97.3% in the classification of test images [3]. In the NFFA-Europe project in 2018 [4], a data set containing 21k SEM images among ten categories was created and used to test the algorithm, which had been pre-trained by another data set obtained from ImageNet Large Scale Visual Recognition Challenge (ILSVRC) 2012. In this project, AlexNet, Inception-v3, Inception-v4, and DenseNet Convolutional Neural Network (CNN) architectures were evaluated in terms of accuracy results, and DenseNet was determined as the most effective one.

In 2020, Aversa et al. conducted a study where they experimented with a novel method that combines supervised and unsupervised learning on SEM (Scanning Electron Microscope) images. In the supervised learning part of this method, Inception-v3 architecture gave the best accuracy result compared to Inception-v4 and Inception-Resnet-v2. In addition, transfer learning and fine-tuning were also combined with Inception-v3, resulting in a significant increase in accuracy, up to 97%. Inception-v3, fine-tuned on the SEM to their test results [5].

III. Materials and Methods

A. Model Training

Models, pre-trained on the ImageNet data set, were used to train the algorithm on the NFFA-Europe data set. A 20/80 test

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rule was applied to all models. While creating the model, it was decided to use the Inception-V3 layers at first. In the initial training, transfer learning was not applied on purpose so as to isolate the Inception-V3 statistics only (see Fig. 1).

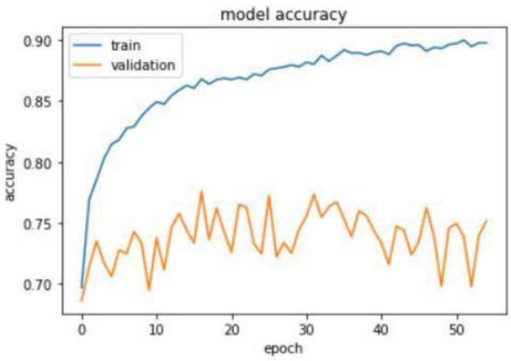


Fig. 1 Statistics for Inception-v3 without Applying Transfer Learning Methods

Next, Inception-V3 was re-trained with 25 epochs and 268 steps per epoch, followed by fine-tuning. After 3 hours of training, approximately 85% validity accuracy was achieved, as represented in Fig. 2. The decrease in the number of epochs did not affect the accuracy as much, and the results began to stabilize after a certain number of epochs. On the other hand, the train accuracy increased steadily.

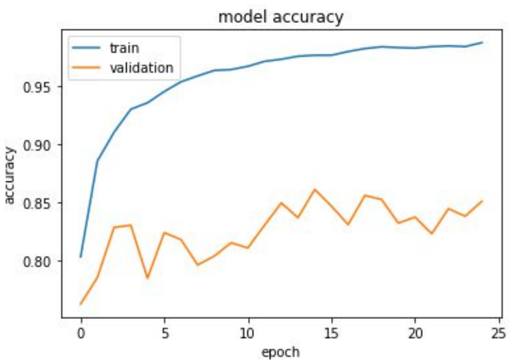


Fig. 2 Statistics for Inception-v3 with Transfer Learning Methods

In another model training, the Inception ResNet-V2 model was trained for about 8 hours using 50 epochs and 1071 steps per epoch. While implementing the model, an Adam optimizer with a 1/4 learning rate was used. The loss type was "Categorical Cross Entropy". Fig. 3 represents that, as a result of this training, 93% accuracy was achieved.

Although the validation accuracy results were acceptable, it was decided to apply the fine-tuning methods due to fluctuating loss values. The first 15 and the last 30 layers were frozen for increasing the accuracy of using ImageNet weights; 0.96% validity accuracy and loss value of 0.21% were obtained due to this change (see Fig. 4).

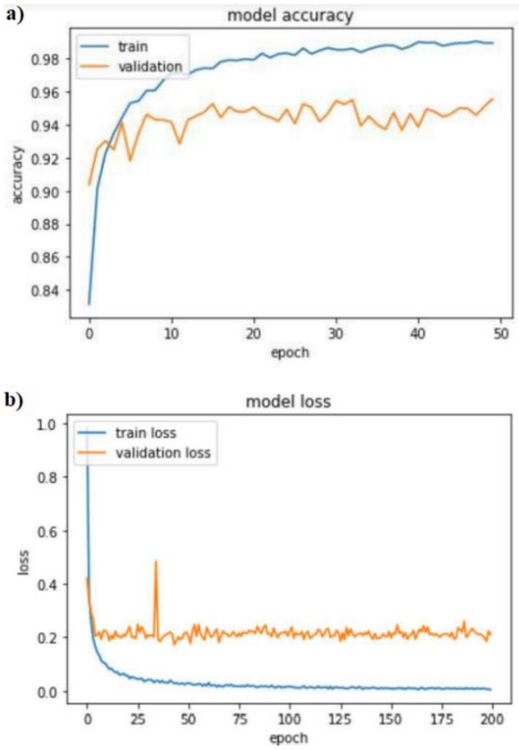


Fig. 3 (a) Model Accuracy Graph for Inception ResNet-V2 without Applying Transfer Learning Methods; (b) Model Loss Graph for Inception ResNet-V2 without Applying Transfer Learning Methods

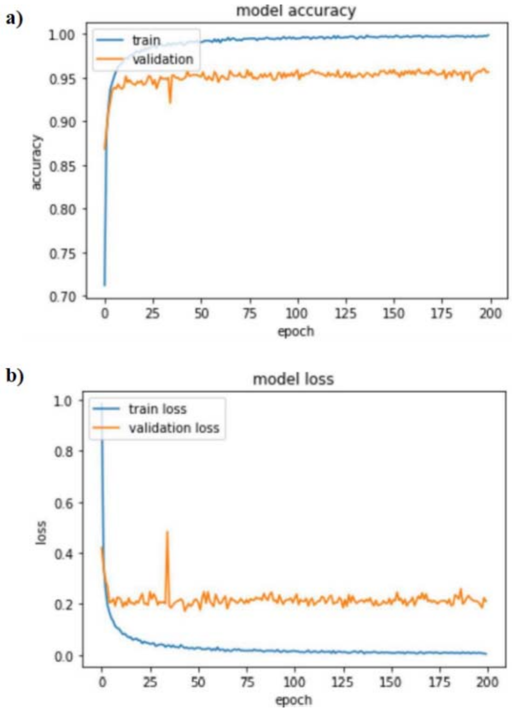


Fig. 4 (a) Model Accuracy Graph for Inception ResNet-V2 with Transfer Learning Methods, (b) Model Loss Graph for Inception ResNet-V2 with Transfer Learning Methods

The results of the model, trained with 200 epochs and the fine-tune method, were better than the previous loss fluctuations; however, considering the confusion matrix represented in Fig. 5, it was concluded that the coated-surface category has a negative impact on the average validation accuracy of the model. According to the test results, this model associated the coated-surface images with the 'particles' category by 12%.

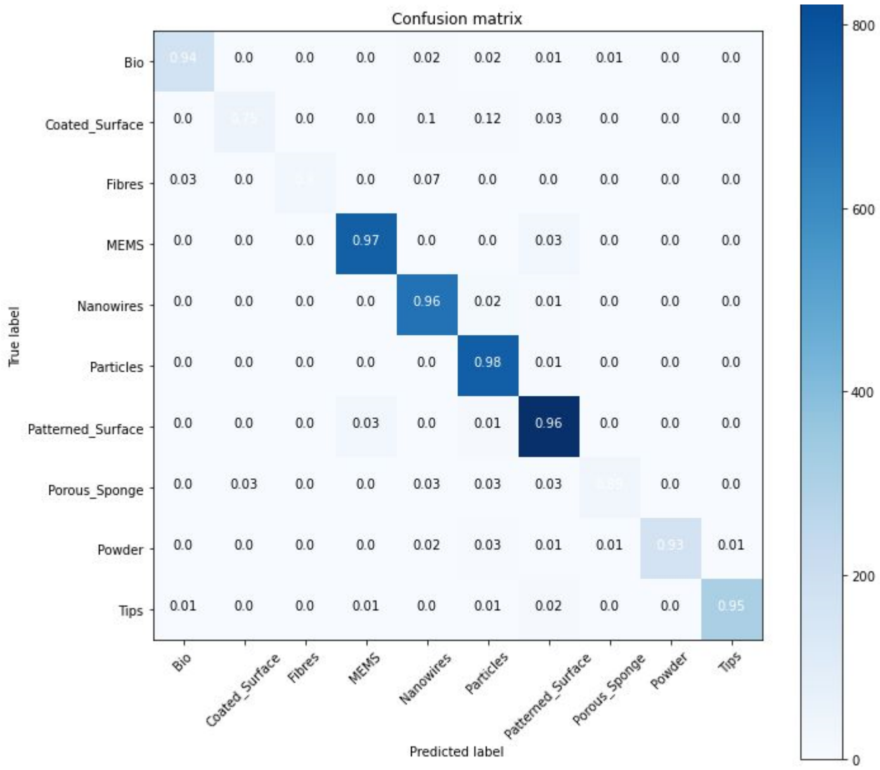


Fig. 5 Confusion Matrix of Inception ResNet-V2 Model with Transfer Learning Applied

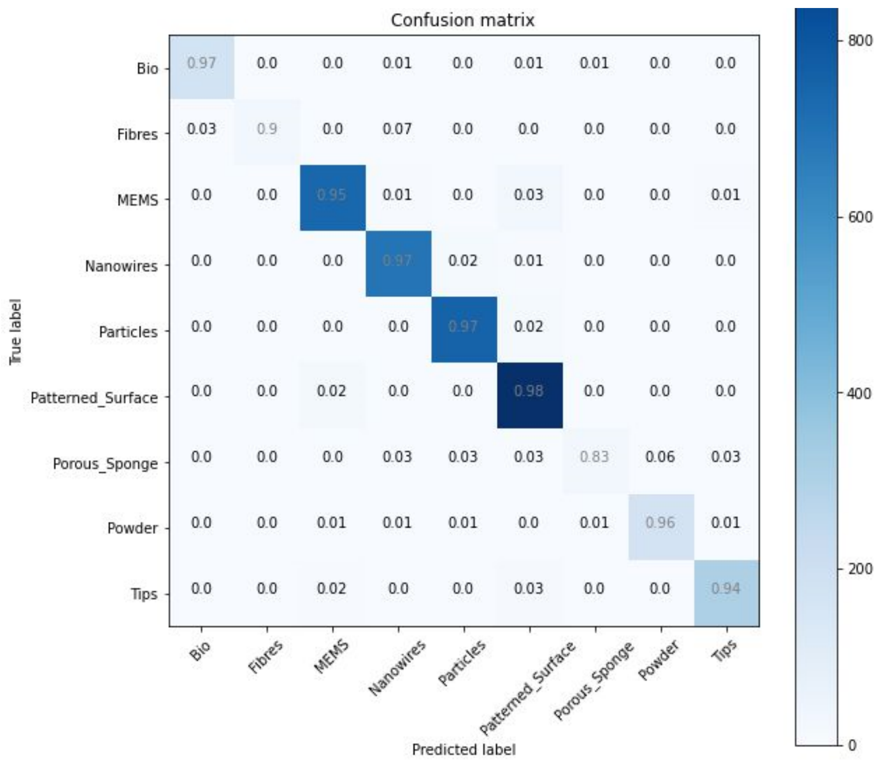


Fig. 6 Confusion Matrix of Inception ResNet-V2 Model with Transfer Learning Methods Applied and Coated Surface Category Removed from Data Set

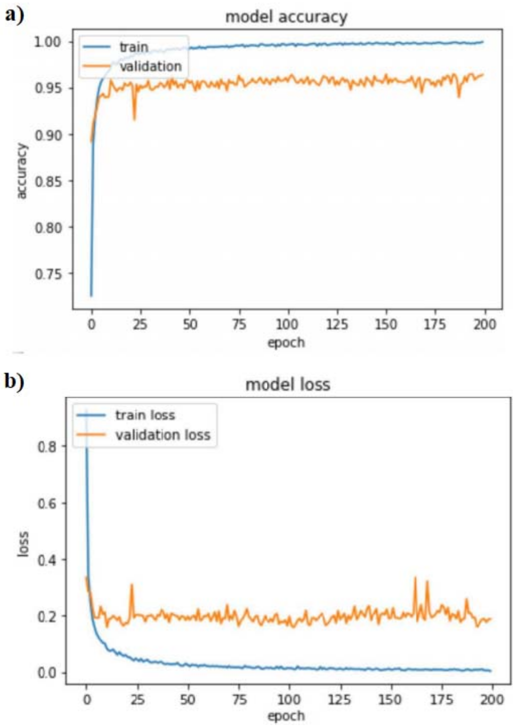


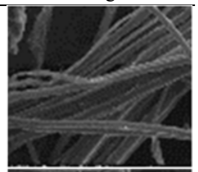
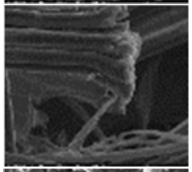
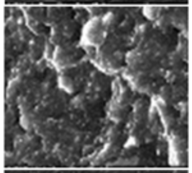
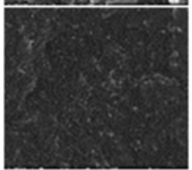
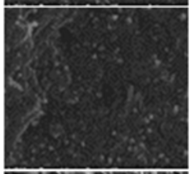
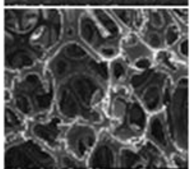
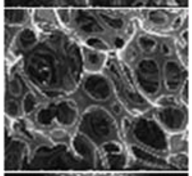
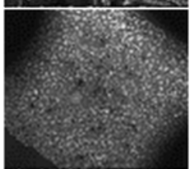
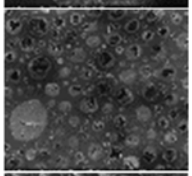
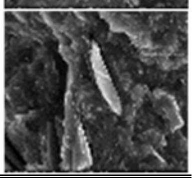
Fig. 7 (a) Model Accuracy Graph for Inception ResNet-V2 Applying Transfer Learning Methods and Coated Surface Category Removed from Data Set; (b) Model Loss Graph for Inception ResNet-V2 Applying Transfer Learning Methods and Coated Surface Category Removed from Data Set

There were approximately 300 images belonging to the coated-surface category in the Nanoscience Foundries and Fine Analysis (NFFA) - Europe data set. This is an insufficient number of images and it affects the accuracy of the model negatively; hence, the removal of the category and re-training. The final validity accuracy result and the loss value obtained were 0.965 and 0.186, respectively. In Figs. 6 and 7, confusion matrix results and the graphs are represented in the absence of the coated-surface category.

B. Model Testing

For manual validation, an additional data set was obtained from the METU in Turkey, yielding no more than 20% of accuracy on the test data. The reason for this decline in the success rate was attributed to training on specific categories, which was not the case when it came to the manual data set. In fact, the classes in this latter set were a mixture of multiple categories already labeled in the NFFA-Europe data set. For example, the 'agricultural waste' category in the manual test data set might include 'bio', 'patterned surface', and 'particles' categories in the NFFA-Europe data set. The testing results appear in Table I.

TABLE I
MANUAL MODEL VALIDATION TESTING RESULTS

Category	Validity Accuracy	Image
Filament	100% nanowires	
Filament	100% nanowires	
Mineral Particle	100% patterned surface	
Nanotube	99% particles	
Nanotube	100% particles	
Polyurethane foam	100% patterned surface	
Polyurethane foam	100% patterned surface	
Polyurethane foam	100% patterned surface	
Polyurethane foam	97% patterned surface	
Mineral in Stratified Structure	100% patterned surface	

C. Implementation of User Interface

To increase the usability of the algorithm, a single-page web application was also developed. For the front-end part of the application, React.js, which is a JavaScript library, was used to make the user interface development easier and faster. The website consists of a drag and drop slot and a button to upload images. The user can upload one or more images. While the system processes the images, a circle continues to go round as notification. Users can view the classification results once the processing is complete. If there exist other images uploaded previously, the system lists both those and newly obtained results.

In the back-end part of the application, Express.js was used as a base for server websites on the Node.js runtime engine. Tensorflow.js was also used to predict uploaded images on the Node.js. The proposed model was saved in HDF5 format on Jupyter notebook since it is identical to Keras models. This is because Tensorflow.js does not allow the use of a model without format conversion. Our model was optimized for being served on the web by sharing the weights into 4 MB files so that browsers can cache them. A sample screenshot from the web application is provided in Fig. 8. The source code of the project can be accessed from https://github.com/keremkurtulus/sem-classifier.

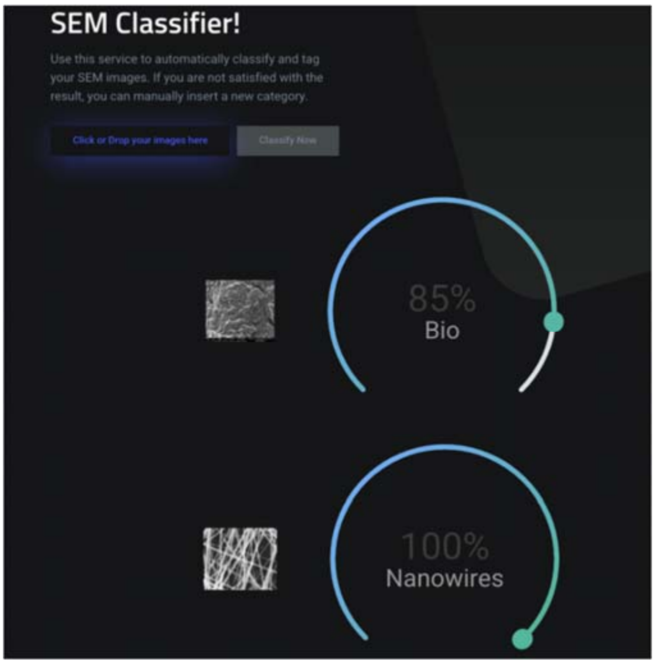


Fig. 8 Page View of the Web Application

IV. Results and Discussions

A. Accuracy Results

In the first model, the Inception-V3 layers were applied without using transfer learning approaches and, at the end of the 4-hour model training, a 76% accuracy rate was achieved upon training with 55 epochs and 528 steps per epoch. Then, the Inception-V3 model was re-trained with 25 epochs and 268 steps per epoch; this time, by applying the fine-tuning method and 3 hours of training, which yielded 85% accuracy. In the next model training, the Inception ResNet-V2 architecture was trained with 50 epochs and 1071 steps per epoch for 8 hours, and the accuracy was 93%. Training the Inception ResNet-V2 was more effective than that of Inception-V3 in terms of accuracy and regardless of applying transfer learning. Besides, the fine-tuned Inception ResNet-V2 model came up with an even better accuracy result upon 200 epochs; the first 15 and the last 30 layers were frozen, increasing the validity 95.5%. However, when the confusion matrix in Fig. 5 was examined, it turned out that the model had associated the coated-surface images with the 'particles' category by 12%, reducing accuracy as a result. After removing the 'coated-surface' category from the data set and applying the same training with the fine-tuned Inception ResNet-V2, the accuracy result was the highest among all trials. Fig. 9 illustrates the architecture diagram of the last model, Inception ResNet-V2 with fine tuning applied and Table II presents the classification report of the model in which the 'coated-surface' category has been removed.

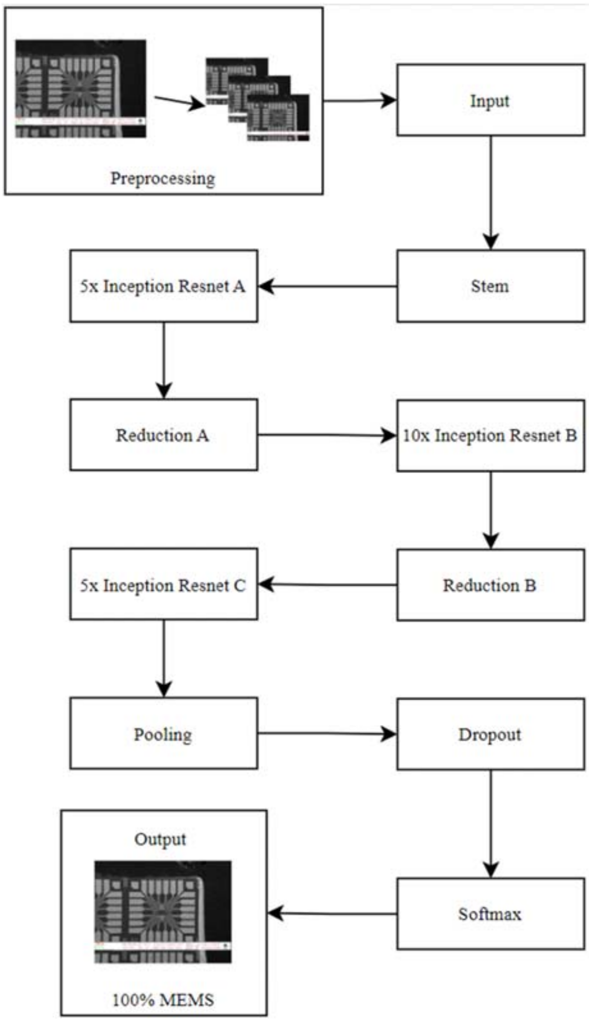


Fig. 9 Architecture of the Fine-tuned Inception ResNet-V2 Model

TABLE II
CLASSIFICATION REPORT OF INCEPTION RESNET-V2 MODEL WITH TRANSFER LEARNING METHODS APPLIED AND 'COATED-SURFACE' CATEGORY REMOVED FROM DATA SET

Categories	Precision	Recall	F1-Score	Support %
Bio	0.98	0.97	0.97	180
Fibers	0.93	0.90	0.92	30
MEMS	0.97	0.95	0.96	779
Nanowires	0.98	0.97	0.97	715
Particles	0.97	0.97	0.97	775
Patterned Surface	0.94	0.98	0.96	964
Porous Sponge	0.94	0.83	0.88	35
Powder	0.96	0.96	0.96	179
Tips	0.96	0.94	0.95	324

B. Data Set Effect on Model Success

The present research further demonstrates the significance of AI in the field of nanotechnology. SEM image classification, being one of the tools in this field, requires dozens of images and different methods to develop new models, not to mention extensive multidisciplinary collaboration to process the outcomes. Nanotechnology is one of those specific fields in which continuous research takes place with not enough data to work with. For this reason, there is urgent need for an open access database for SEM images from different fields to find general patterns and specific ones. Additionally, further information is required concerning the internal structure of materials, along with corresponding images to conduct more advanced research.

V. CONCLUSION

The present paper is an attempt to classify SEM images in the field of nanotechnology by introducing a model with high accuracy and using a combination of the most advanced and newly released methods. To develop a model in any field of nanoscience, large data sets are a mandatory requirement, whose shortage posed a major challenge to the present study. To compensate, the NFFA-EUROPE - 100% SEM data set was used to develop the model with 80-20 training and testing percentages. Also, data augmentation techniques were used to enlarge the data set. Later on, an additional data set obtained from the METU in Turkey was used to validate the accuracy.

This study provides a deep learning model that classifies SEM images and a web application to perform the classification. Doing so among ten categories, this model achieved 95.5% success, while it was observed in the confusion matrix that the 'coated-surface' category had a negative effect on the model's success. Both the low number of images in this category and the 12% similarity with the other categories reduced the accuracy, leading to the removal of the 'coated-surface' category. The fine-tuned Inception ResNet-V2 model was re-trained in the absence of this category and among all the methods trained, the highest accuracy result of 96% was obtained. Another benefit of this model is that, in its web application format SEM images can be classified simultaneously within a simple, user-friendly interface.

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