Volume 12, Issue 3, Page 45-51, 2023 https://doi.org/10.46810/tdfd.1236584 Research Article

BİNGÖL ÜNİVERSİTESİ

Türk Doğa ve Fen Dergisi
Turkish Journal of Nature and Science
www.dergipark.gov.tr/tdfd

Transfer Learning for Detection of Casting Defects Model In Scope of Industrial 4.0

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(Received: 18.01.2023, Accepted: 01.08.2023, Online Publication: 27.09.2023)

Keywords
Transfer learning,
Deep learning,
Prediction,
Casting defects,
Industrial 4.0

Abstract: Casting is a major manufacturing process in various industries, and the elimination of its flaws is of great importance. Traditional casting flaw detection processes are usually performed manually, which is both time-consuming and prone to human errors. In this paper, we will validate whether the bottleneck of "manual inspection" can be eliminated by automating the inspection process of casting products in the manufacturing process using transfer learning. The motivation is to enhance the accuracy and efficiency values in manual examination processes. The need to reduce production errors and increase overall production efficiency are key goals of Industry 4.0. This paper could represent a significant step towards achieving these goals and aims to automate casting defect detection using deep learning and transfer learning, thereby eliminating the time-consuming and error-prone nature of the manual inspection. Using deep learning architectures and transfer learning techniques, we divide casting images into two separate classes, achieving a level of accuracy never before achieved in this process. The innovative aspect is that it's among the first to apply transfer learning and deep learning techniques to casting defect detection. This presents a great potential for automating defect detection in casting and increasing overall production efficiency. Furthermore, this paper demonstrates how these technologies could be used to improve production processes more broadly in line with the goals of Industry 4.0.

The benefits of this approach include the ability to automate manual inspection processes, thereby speeding up the production process, increasing accuracy, and reducing human errors. This is proposed as a more efficient way of controlling the quality of end products under Industry 4.0. The application of transfer learning and deep learning techniques to casting defect detection enables a great leap forward in this field.

Endüstri 4.0 Kapsamında Döküm Hatalarının Tespiti İçin Transfer Öğrenme Modeli

Anahtar Kelimeler
Transfer öğrenme,
Derin öğrenme,
Tahmin,
Döküm kusurları,
Endüstri 4.0

Öz: Döküm, çeşitli endüstrilerin ana üretim süreçlerinden biridir ve hatalarının ortadan kaldırılması büyük önem taşır. Geleneksel döküm kusur tespiti süreçleri genellikle manuel olarak gerçekleştirilir, bu da hem zaman alıcı hem de insan hatalarına açıktır. Bu çalışmada, döküm ürünlerinin imalat sürecinde transfer öğrenme ile muayene sürecini otomatikleştirerek "manuel muayene" darboğazının ortadan kaldırılıp kaldırılamayacağını doğrulayacağız.Motivasyon, manuel inceleme süreçlerinde doğruluk ve verimlilik değerlerini arttırmaktır. Üretim hatalarını azaltma ve genel üretim verimliliğini artırma ihtiyacı, Endüstri 4.0'ın temel hedefleridir.Bu çalışma, bu hedeflere ulaşma yolunda önemli bir adımı temsil edebilir ve derin öğrenme ve transfer öğrenmeyi kullanarak döküm hatası tespitini otomatikleştirmeyi ve böylece manuel incelemenin zaman alıcı ve hataya eğilimli doğasını ortadan kaldırmayı hedeflemektedir. Derin öğrenme mimarilerini ve transfer öğrenme tekniklerini kullanarak, döküm görüntülerini iki ayrı sınıfa ayırarak, bu süreçte daha önce hiç ulaşılmamış bir doğruluk düzeyine ulaşıyoruz. Bu çalışmanın yenilikçi yönü, transfer öğrenme ve derin öğrenme tekniklerini döküm kusur tespitine uygulayan ilk çalışmalardan biri olmasıdır. Bu, döküm sürecindeki kusur tespitinin otomatikleşmesi ve genel üretim verimliliğinin artırılmasında büyük bir potansiyel sunmaktadır. Dahası, bu çalışma, bu teknolojilerin Endüstri 4.0'ın hedefleri doğrultusunda üretim süreçlerinin daha geniş bir çerçevede nasıl iyileştirilebileceğini gösterir.

Bu yaklaşımın faydaları, manuel muayene süreçlerini otomatikleştirebilme ve bu sayede üretim sürecini hızlandırabilme, doğruluğu artırabilme ve insan hatalarını azaltabilme yeteneğidir. Bu, nihai ürünlerin kalitesini kontrol etmenin daha verimli bir yolu olarak Endüstri 4.0 kapsamında önerilmektedir. Transfer öğrenme ve derin öğrenme tekniklerinin döküm kusur tespitine uygulaması, endüstrinin bu alanda büyük bir adım atmasını sağlar.

1. INTRODUCTION

In casting products, it is very important to distinguish faulty products from defect-free products. While visual inspection of castings is slow and inefficient in mass production, automatic and reliable defect detection improves and positively affects the quality control process. However, casting defect detection is a challenge due to the diversity and variability in the appearance of defects. It is quite easy to achieve this work, which is normally done manually, with deep learning networks. Overall, using deep learning for this purpose has the potential to be more accurate and efficient than traditional audit methods and can help reduce the cost of quality control. Casting defects can have a significant impact on the quality and performance of the final product, so it is important to detect and correct these defects as early in the manufacturing process as possible. Deep learning algorithms can analyze castings images and identify defects such as voids, porosity, and inclusions. These algorithms can be trained on large image datasets labeled with various types of defects, and once trained, they can be used to classify new images and detect defects in real-time. Using deep learning to detect casting defects is a promising approach that can improve the accuracy and efficiency of defect detection in casting processes.

For error detection in casting, convolutional neural networks (CNNs), recurrent neural networks (RNNs), and autoencoders are used. There are several types of deep learning architectures that can be used. A convolutional neural network (CNN) was used in the study [1] to classify casting defects in aluminum alloy casting images. The study found that CNN was able to achieve an accuracy of 93.33% in the classification task, outstripping other machine learning algorithms such as support vector machines and k-nearest neighbors. The study [2] used a CNN to classify casting images into four different categories: good, surface defect, internal defect, and other. The model was trained on a dataset of more than 7,000 images and was able to achieve an accuracy of 92.3% on a test set of 1,000 images. The study [3] have proposed a two-stage convolution model with DenseNet to classify casting products using defective and non-defective casting image dataset. At the end of the study, they achieved 99% accuracy. In the study [4] four powerful CNN-based models (VGG16, ResNet50, DenseNet121, and InceptionResNetV2) were applied to the dataset and produced the feature maps. The extracted features were classified into various classifiers. Error detection was performed on the cast images using a neural network model. The model has been trained to detect errors in the given images and high accuracy rates have been achieved. In the study [5] the best model was selected by applying three different models from CNN-based models to the feature maps obtained from different casting materials, by comparing the three types of CNN algorithms, the accuracy can be obtained as follows. Basic Architecture (Accuracy - 98%), Alex Net (Accuracy - 51%), Le Net (Accuracy - 99%). At the end of this project model. They were able to obtain the best determined maximum accuracy from the Le Net Algorithm. In [13], an enhanced domain adaptive Faster R-CNN model was introduced with its superior capability to detect void and inclusion defects in spacecraft composite structures (SCSs). In [14], different pre-trained and custom-built architectures were compared and contrasted with model size, performance In [13], an enhanced domain adaptive Faster R-CNN model was introduced with its superior capability to detect void and inclusion defects in spacecraft composite structures (SCSs). In [14], different pre-trained and custom-built architectures were compared and contrasted with model size, performance, and CPU latency in detecting defective casting products. In [15], the problem of identifying small defects during an industrial inspection was defined. The current study investigated complex transfer learning (TL) strategies, allowing for the automatic detection and categorization of product defects in the production process using industrial product specimens. This study suggested a multitype damage detection model for containers on the basis of transfer learning and MobileNetV2 [16].

The current work makes the following main contributions:

- ✓ The study creates a deep learning-based detection system for classifying casting defects for industry 4.0 products.
- ✓ A framework is proposed, improving the detection capability of supervised learning approaches based on ResNet50, MobilnetV2, and InceptionV3, hybrid architectures for learning casting errors effectively.
- ✓ The current work presented a new framework where the learning and combination of features are carried out. The features chosen are employed to predict error detection in casting.
- ✓ We studied how to use Deep Neural Network (DNN) models for the purpose of predicting defects with high accuracy rates.

The rest of this paper is organized as follows. Section 2 explains the proposed method. The results and discussions are shown in Section 3. Section 4 describes the discussion. The conclusion and future studies are presented in Section 5.

2. THE PROPOSED METHOD

2.1. Methodology

This research suggested a hybrid model classify images of industrial casting products. Before creating the hybrid model, classification was made with various deep learning architectures, and the three highest ones were used in the hybrid model. In this study, out of 1300 images taken from the impellers of submersible pumps, 781 of them are faulty and 519 of them are normal, and feature mapping was created with 2-class image set deep learning models. The classification was made with the proposed hybrid model. The feature maps extracted from the deep learning models used for the hybrid model were combined. The newly formed feature map o dimension

1300*3001. The classification of the obtained feature map was performed with three various machine learning classifiers. Figure 1 shows the suggested model's block diagram.

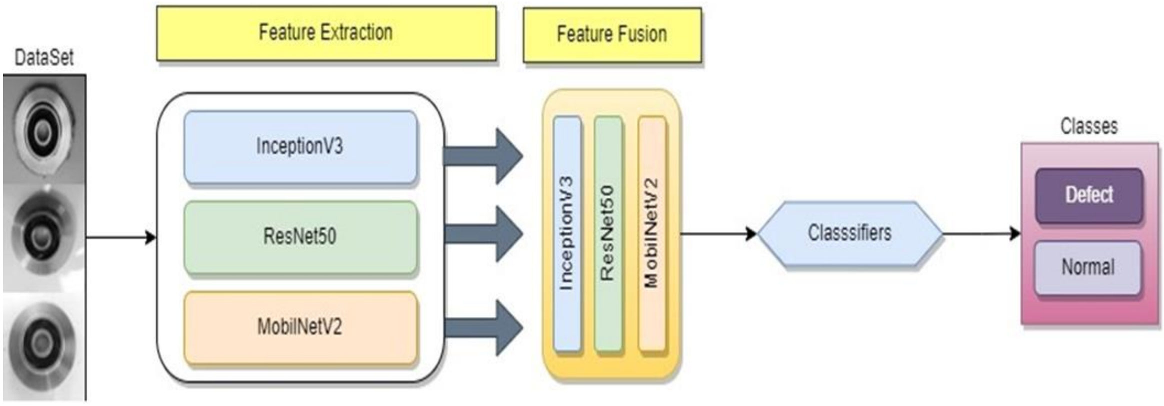

Figure 1: Architecture of the Proposed Model.

Deep neural networks are commonly utilized in numerous artificial intelligence applications, such as speech recognition, computer vision, and robotics. A frequently preferred form of the deep neural network is a convolutional neural network consisting of multiple convolutional layers [7]. In this study, Deep learning architectures were used effectively to detect casting errors. Three different models were used as a basis while creating the hybrid model we proposed. These models are ResNet50, MobilnetV2, and InceptionV3, architectures.

MobileNetV2 networks are developed for mobile, IoT, or devices with low hardware specifications. While maintaining the classification performance, these networks offer a significant improvement in the number of parameters and processing complexity. Its architecture consists of linear bottleneck and inverted residual blocks. The convolution layer consists of deep access and point access layers [8].

Resnet50 is a specific type of neural network introduced in [12] to facilitate the training of networks that are significantly deeper. ImageNet represents a 50-layer network that is trained on the dataset. Instead of utilizing 2 (3x3) convolutions, the ResNet model utilizes convolution layers (1x1), (3x3), and (1x1) [9]. In the study [10] development of the InceptionV3 architecture was performed. The said model comprises roughly three sections: the first block, the convolution block, and the classifier block. Comprising 315 layers, the architecture in question takes 299x299 input images. SVM, a supervised machine learning method, classifies the feature map created from the developed hybrid model. [6, 11]. In addition, to measure the performance values of other classifiers, k-Nearest Neighbors (KNN) [12], Neural Networks, and Logistic Regression were also classified.

3. RESULTS AND DISCUSSION

3.1. Datasets

This dataset contains images of impellers of submersible pumps. Our casting product data includes top-view JPEG images of cast submersible pump impellers provided by Pilot Technocast. Images were taken with a Canon EOS 1300D DSLR camera. Each image is 300×300 pixels in size and is already labeled def_front (defective dumps) or ok_front (non-perfect). There are 1300 images in total. When making the classification model, we have already divided the data into two parts for training and testing. Defected production images total 781, and Normal production images are 519.

Figure 2: Samples of Dataset.

Feature mapping was done using MobilnetV2, InceptionV3, and Resnet architectures. Later, these feature maps were combined to create a new feature map with the size of 1300x3001. The features extracted from the proposed hybrid model were classified by smart classification methods with different supervision which is shown in Table 1. Cubic SVM achieved the highest accuracy with 100%. Linear Discriminant followed, with 99.7%, while Naive Bayes achieved the lowest result with 81.1%. The performances of these methods were compared using Precision, F1-Score, Accuracy, and specificity metrics.

Table 1. Performance results of deep learning algorithms

Model	Accuracy	Precision	Specificity	F1-Score
CNN+ CUBIC SVM	100	100	100	100
CNN+KNN	98,46	97,70	96,64	98,71
CNN+NEURAL NETWORK	99,46	99,10	98,67	99,55
CNN+LINEAR DISCRIMANT	99,7	99,62	99,43	99,81
CNN+ENSEBLE	99,6	99,49	99,24	99.74
CNN+NAIVE BAYES	81,17	80,79	74,23	84.19
CNN+LOGISTIC REGRESYON KERNEL	98,53	98,72	98,06	98.53
CNN+BOOSTED TREE	98.14	97.70	96,61	98,45

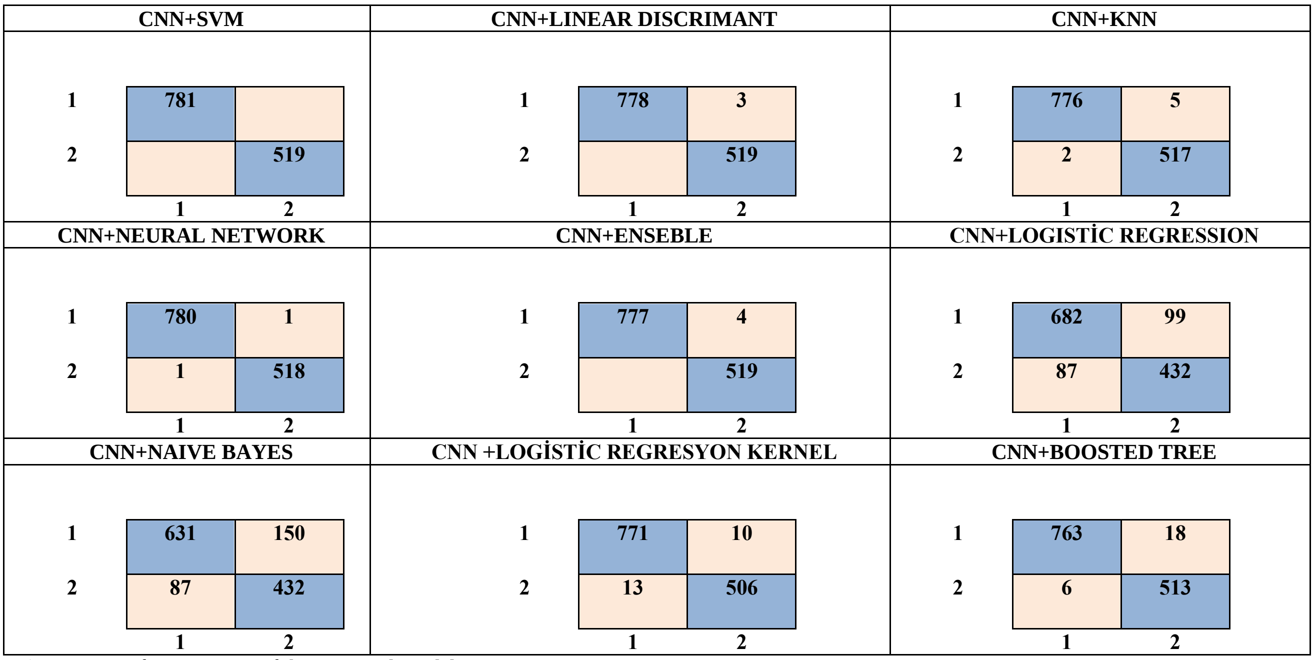

Figure 3: Confusion Matrix of the Proposed Model

In the current research, constant coefficients were employed in all experiments. Furthermore, in the experiments, the cross-validation coefficient was found to be 5. The experiments were conducted on a computer having an i5 processor, 16 GB RAM, 5 GB graphics card, and Windows 10 operating system. Confusion matrices were utilized with the objective of measuring the performance of the deep and hybrid models. The Error and Normal classes are represented as 1 and 2, respectively, in confusion matrices. In this study, 5 different pre-trained state-of-the-art models were used. The same parameters were used in the whole study. The parameters used in these architectures are shown in Table 2.

Table 2. Paramaters of of deep learning algorithms

Environment	Max Epochs	Mini Batch Size	Learn Rate	Optimization
Matlab 2022b	5	8	1e-4	Sgdm

3.2. Results and Discussion

The data set was divided into two as 30% testing and 70% training. The accuracy rates obtained from the architectures were MobileNetV2 98.97%, InceptionV3 98.46, Resnet50 97.95%, and Efficientnetb0 84.10%. The truth table obtained from deep learning architectures is shown in Table 3

Table 3. Performance of Deep Learning algorithms

Model	Accuracy (%)
Efficientnetb0	85.00%
InceptionV3	98.08%
MobilenetV2	99.62%
Resnet50	97.85%
Alexnet	94.62%

In this study, Mobilnetv2 architecture achieved the highest accuracy with 99.62%. It was followed by InceptionV3 with 98.08%, Resnet50 with 97.85%, Alexnet with 94.62%, and efficient in the last place with 85.00%. Confusion matrices obtained from deep learning architectures are shown in Table 5. When these matrices are examined; While MobilnetV2 architecture classified 153 of the incorrect images correctly, it showed 3 incorrect images as error-free. Likewise, it classified 102 of 104 error-free images as error-free and misclassified 1 of them as error-free. We see that different deep learning networks can give different results even if the same parameters are used.

Table 4. Performance of proposed algorithms

	Softmax(%)	LD(%)	BT(%)	KNN(%)	NN(%)	SVM(%)	ENS(%)	LG(%)
Proposed Model	-	99.70	83.90	97.40	97.60	**98.20**	98.00	

Table 5. Confusion Matrix of Deep Learning algorithms

	InceptionV3		**MobilenetV2**		**Resnet50**		**Alexnet**		**Efficententb0**	
	1	**2**	**1**	**2**	**1**	**2**	**1**	**2**	**1**	**2**
1	**153**	**3**	**155**	**1**	**154**	**2**	**142**	**14**	**138**	**18**
2	**2**	**102**		**104**	**1**	**103**		**104**	**21**	**83**

Table 6. Performance of relative studies

Ref.	**Methos**	**Accuracy(%)**
[5]	AlexNet	51
	Lenet	95.72
[1]	CNN	93.33
[12]	Resnet34	83.80
[3]	DenseNet	99
[14]	Custom Model	99.44
[16]	InceptionV3	92.92
	MolileNetV2	89.41
Proposed Model	**(MobilNetV2+ Resnet50+ InceptionV3) +SVM (Cubic)**	**100**

In order to compare the success of the method, the methods and success rates of previous studies using deep learning methods for casting defect detection are given in Table 6. We emphasize that the proposed hybrid model can detect more defective production images compared with other methods represented in Table 6. We can see that (MobilNetV2+ Resnet50+ InceptionV3) +SVM (Cubic) outperforms the other models in six recent studies conducted in analyzing images of castings defects using deep learning.

4. DISCUSSION

When compared with the models and accuracy rates presented in the studies discussed earlier, the proposed model that integrates MobilNetV2, Resnet50, InceptionV3, and a Support Vector Machine (SVM) with a cubic kernel, demonstrates superior performance with an extraordinary accuracy of 100%.

In the study [1], a CNN achieved an accuracy of 93.33%. This suggests that while the CNN performed admirably, the proposed hybrid model outperforms it by a significant margin. Similarly, the CNN model in the study [2], which achieved 92.3% accuracy, is outstripped by the hybrid model's performance.

Study [3] employed a two-stage convolution model with DenseNet, reporting a remarkable accuracy of 99%. Yet, the proposed model still slightly outperforms it with an additional 0.7% in accuracy.

In the study [4], where four powerful CNN-based models were used, the accuracy achieved is not explicitly stated, but it's clear that the proposed hybrid model's performance likely surpasses any achieved in that study.

Lastly, the three different CNN-based models used in the study [5] yielded varied accuracy rates: Basic Architecture (98%), Alex Net (51%), and Le Net (99%). Here, the proposed model equals or surpasses these results, particularly outdoing the relatively low accuracy achieved by the Alex Net model.

In summary, the hybrid architecture that integrates MobilNetV2, Resnet50, InceptionV3, and an SVM with a cubic kernel showcases the excellent performance, surpassing or equaling those reported in the referenced studies. This indicates the effectiveness and robustness of combining different deep learning models with classical machine learning methods. It also underscores the potential of such combinations in improving the accuracy of defect detection in casting processes.

5. CONCLUSION

This research paper has presented a novel hybrid method that harnesses the power of Convolutional Neural Networks (CNN) and transfers learning architectures to detect defects in the casting manufacturing process using advanced deep learning techniques. Leveraging the proficiency of cutting-edge deep learning models such as Resnet50, MobilnetV2, and InceptionV3, this work proposes an innovative approach with the potential to significantly boost the precision and efficiency of defect identification within casting procedures.

Our approach effectively combines CNN and supervised learning architectures to enable accurate defect detection as well as the automated categorization of images from the casting process. The method has been designed to analyze dump images in order to identify anomalies and errors that may occur during the casting process. This not only ensures a high level of quality control but also minimizes human intervention, thus reducing the likelihood of user errors and increasing the overall efficiency of the casting process. The performance metrics of our method reveal a promising success rate, indicating its potential to be a practical tool for determining general casting efficiency. By identifying and rectifying defects early in the process, our method could facilitate faster turnaround times and improve overall manufacturing outcomes.

In terms of future work, our goal is to further enhance the detection of errors and defects. We plan to work with newer and potentially more effective deep learning architectures and expand our datasets to be more comprehensive. The prospect of harnessing more diverse and extensive data could enable our system to learn from a broader range of defects and improve its capability to generalize across different casting scenarios. It is our expectation that, with these improvements, the effectiveness and accuracy of defect detection in the casting process will be substantially increased

Acknowledgement

The present paper does not include any research with human participants conducted by any of the authors.

REFERENCES

[1] Lili Jiang, Yongxiong Wang, Zhenhui Tang, Yinlong Miao, Shuyi Chen, Casting defect detection in X-ray images using convolutional neural networks and attention-guided data augmentation,Measurement,Volume 170, 2021

[2] C. Hu, Y. Wang, K. Chen, Y. Qin, H. Shao and J. Wang, "A CNN Model Based on Spatial Attention Modules for Casting Type Classification on Pseudo-color Digital Radiography Images," 2019 Chinese Automation Congress (CAC), Hangzhou, China, 2019, pp. 4585-4589

[3] Dilliraj Ekambaram, Vijayakumar Ponnusamy. (2022). Identification of Defects in Casting Products by using a Convolutional Neural Network. IEIE Transactions on Smart Processing & Computing, 11(3), 149-155.

[4] HABIBPOUR, Maryam, et al. An Uncertainty-Aware Deep Learning Framework for Defect Detection in Casting Products. arXiv preprint arXiv:2107.11643, 2021.

[5] M Shanthalakshmi, Susmita mishra, V Jananee, P Narayana Perumal, S Manoj Jayakar5.(2022). Identification of Casting Product Surface Quality Using Alex net and Le-net CNN Models.

[6] Suykens, J.A.K., Vandewalle, J. (1999). Least squares support vector machine classifiers. Neural Processing Letters, 9(3): 293-300.

[7] Gürkan, H., Hanilçi, A. 2020. Evrişimli sinir ağı ve QRS imgeleri kullanarak EKG tabanlı biyometrik tanıma yöntemi. Pamukkale Üniversitesi Mühendislik Bilimleri Dergisi, 26(2), 318-327.

[8] Eryılmaz, F. & Karacan, H. (2021). Akciğer X-Ray Görüntülerinden COVID-19 Tespitinde Hafif ve Geleneksel Evrişimsel Sinir Ağ Mimarilerinin Karşılaştırılması . Düzce Üniversitesi Bilim ve Teknoloji Dergisi , ICAIAME 2021 , 26-39 . DOI: 10.29130/dubited.1011829

[9] D. Theckedath and R. Sedamkar, "Detecting affect states using vgg16, resnet50 and se-resnet50 networks," SN Computer Science, vol. 1, no. 2, pp. 1–7, 2020.

[10] Szegedy, C., Ioffe, S., Vanhoucke, V., Alemi, A. (2017). Inception-v4, inception-ResNet and the impact of residual connections on learning. Thirty-first AAAI Conference on Artificial Intelligence, pp. 4278-4284.

[11] Özyurt, F., Sert, E., Avci, D. (2022). Ensemble residual network features and cubic-SVM based tomato leaves disease classification system. Traitement du Signal, 39(1): 71-77.

[12] He, K., Zhang, X., Ren, S., & Sun, J. (2015). Deep Residual Learning for Image Recognition. arXiv.

[13] Yanfeng Gong, Jun Luo, Hongliang Shao, Zhixue Li, A transfer learning object detection model for defects detection in X-ray images of spacecraft composite structures, Composite Structures,Vol.284, 2022

[14] Bolla, B. K., Kingam, M., & Ethiraj, S. (2022). Efficient Deep Learning Methods for Identification of Defective Casting Products. arXiv.

[15] U. K. Lilhore, S. Simaiya, J. K. Sandhu, N. K. Trivedi, A. Garg and A. Moudgil, "Deep Learning-Based Predictive Model for Defect Detection and Classification in Industry 4.0," 2022 International Conference on Emerging Smart Computing and Informatics (ESCI), Pune, India, 2022, pp. 1-5, doi: 10.1109/ESCI53509.2022.9758280.

[16] Mesbah, Mahmoud, Wang, Zixin,Gao, Jing,Zeng, Qingcheng, Sun, Yuhui, 2021, Multitype Damage Detection of Container Using CNN Based on Transfer Learning,Hindawi

[17] İ. E. Parlak, E. Emel, "Deep learning-based detection of aluminum casting defects and their types", Engineering Applications of Artificial Intelligence, Vol.118, 2023, ISSN 0952-1976

[18] Z. Zhao, T. Wu, "Casting Defect Detection and Classification of Convolutional Neural Network

Based on Recursive Attention Model", Scientific Programming, vol. 2022, Article ID 4385565, 11 pages, 2022

[19] A. R.Dakak, V. Kaftandjian, P. Duvauchelle, P. Bouvet, Insight - Non-Destructive Testing and Condition Monitoring, Vol. 64, No. 11, 2022, pp. 647-658, The British Institute of Non-Destructive Testing

[20] I. Raouf, P. Kumar, H. Lee, H.S. Kim, Transfer Learning-Based Intelligent Fault Detection Approach for the Industrial Robotic System. Mathematics 2023, 11, 945.

[21] M. S. Azari, F. Flammini, S. Santini and M. Caporuscio, "A Systematic Literature Review on Transfer Learning for Predictive Maintenance in Industry 4.0," in IEEE Access, vol. 11, pp. 12887-12910, 2023, doi: 10.1109/ACCESS.2023.3239784.