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A convolutional neural network (CNN) for defect detection of additively manufactured parts

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A CONVOLUTIONAL NEURAL NETWORK (CNN) FOR DEFECT DETECTION OF ADDITIVELY MANUFACTURED PARTS

by

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ABSTRACT

Additive manufacturing (AM) is a layer-by-layer deposition process to fabricate parts with complex geometries. The formation of defects within AM components is a major concern for critical structural and cyclic loading applications. Understanding the mechanisms of defect formation and identifying the defects play an important role in improving the product lifecycle. The convolutional neural network (CNN) has been demonstrated to be an effective deep learning tool for automated detection of defects for both conventional and AM processes. A network with optimized parameters including proper data processing and sampling can improve the performance of the architecture. In this study, for the detection of good deposition quality and defects such as lack of fusion, gas porosity, and cracks in a fusion-based AM process, a CNN architecture is presented comparing the classification report and evaluation of different architectural settings and obtaining the optimized result from them. Since data set preparation, visualization, and balancing are very important aspects in deep learning to improve the performance and accuracy of neural network architectures, exploratory data analysis was performed for data visualization and the up-sampling method was implemented to balance the data set for each class. By comparing the results for different architectures, the optimal CNN network was chosen for further investigation. To tune the hyperparameters and to achieve an optimized parameter set, a design of experiments was implemented to improve the performance of the network. The performance of the network with optimized parameters was compared with the results from the previous study. The overall accuracy (>97%) for both training and testing the CNN network presented in this work transcends the current state of the art (92%) for AM defect detection.

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1. INTRODUCTION

1.1. BACKGROUND

The evolution of industries depends on innovative and cutting-edge research activities associated with manufacturing processes, materials, and product design. Manufacturing processes can be categorized into five categories, namely, subtractive, additive, joining, dividing, and transformative. The terminologies such as 3D printing (3DP), rapid prototyping (RP), direct digital manufacturing (DDM), rapid manufacturing (RM), and solid freeform fabrication (SFF) can be used to describe additive manufacturing processes. Additive manufacturing (AM), also known as 3D printing, is a transformative approach to industrial production that enables the creation of lighter, stronger parts and systems [2, 3, 4, 5, 6, 7, 8]. It is another technological advancement made possible by the transition from analog to digital processes. AM can bring digital flexibility and efficiency to manufacturing operations. Moreover, AM in contrast to conventional production processes consists of additional controllable process parameters and higher active interaction between the material properties and process parameters.AM can be categorized in numerous ways based on the functional framework of the material. Although the methods of classification can also include the patterning energy, the technique of generating primitive geometry, the nature of used materials, and the support procedure. Among different AM processes recently digital light processing (DLP), electron beam melting(EBM), selective laser sintering(SLS), laser metal depositing(LMD) have gained much attention in the research and industrial sector [9]. There are many AM applications including lightweight products for the aerospace, automotive, medical, architectural modeling, and energy industries. These include applications where low volume production, high design complexity, and the ability to change designs frequently are needed. Alongside having many more advantages using Am in the modern manufacturing process there are still some challenges that hinder the wide range adaption of AM in many sectors. Some of the disadvantages of 3D printing are being very expensive for the extreme cost of equipment and material cost. The surface finish of the manufactured part still poses a challenge in AM process. Also, some AM process tends to be slow and consist of their own size limitations.

However, It is observed that none of these technologies are ideal in every dimension. Defect formation in the additively manufactured parts is one of the main challenges in this rapidly evolving technology. Some of the defects observed in fusion-based processes include lack of fusion, keyhole collapse, gas porosity, solidification cracking, solid-state cracking, and surface-connected porosity. Without optimized processing parameters, defects can often occur in parts produced with AM. These defects can potentially lead to failures of AM parts. The microstructure has a direct effect on a material's physical and mechanical properties [10, 11, 12, 13, 14]. Pores in an AM part can be either undesirable defects in the solid phase contributing to the failure of the system or intentionally designed pore structures for special applications. Characterizations of both types of porosity are important to predict the mechanical properties of the structure [15]. Gas pores are spherical pores occurring due to gas trapped in the raw metal powder particles or trapped environmental inert gas during the melting process. LOF porosity is the most frequently discussed defect because its large size and irregular morphology make it particularly deleterious to mechanical properties. The formation of the LOF defects is because the metal powders are not fully melted to deposit a new layer on the previous layer with sufficient overlap [15]. Internal cracks are common defects that appear in AM components and mainly result from thermal stresses. Cracks typically generate when continuous and semi-continuous liquid films form on the grain boundaries of the heat-affected zone and when tensile stresses are from within parts [15]. During the manufacturing process, once a crack has occurred, it spreads along with the molten layer, significantly affecting the mechanical properties of the component, and even risking its disposal. Melt ball formation, a.k.a. balling, occurs when molten material solidifies into spheres instead of solid layers, which is a severe impediment to inter-layer connection. Generally, balling formation occurs when spherical particles are produced in the component due to interactions between the molten pool and the metal powder [15]. This happens under the influence of the manufacturing environment and prevents the full melting of some powder particles that mix within the component. Metal balls form independently and are easily generated in the layer-by-layer scanning process, resulting in a rough, bead-shaped surface that produces irregular layer deposition that adversely affects the density and quality of the part. In addition, balling also affects the normal operation of the powder spreading roller, and in severe cases can hinder the spreading mechanism. Balling can increase the surface roughness of the component and reduce its density and mechanical properties. In AM processes, the temperature of the metal powder varies considerably, and thermal stresses easily from within the component, causing significant uncertainty with regards to the quality of the final part. When the stresses trapped inside the component are suddenly released, cracks emerge on the surface, affecting the performance and life of the component. Residual stresses have been associated with two different mechanisms, including the cool-down phase of molten top layers and the thermal layers and the thermal gradient mechanism [15]. So, understanding the different defect formations with their proper identification throughout the process is very crucial in AM part processing.

1.2. RESEARCH OBJECTIVES

Recently AM technology has been relatively successful at attaining sufficient mechanical properties, defects, and geometric inaccuracy still limit component adoption in the industry. At the same time defects often occur inbuilt components due to discontinuities in the printing process and other extraneous factors. Therefore precise detection and localization of these defects play a crucial role in the modern additive manufacturing process. As a result, defect detection technologies have been widely used in AM processes. Methods of detecting metal AM defects can be divided into traditional non-destructive defect detection technology and defect detection technology based on machine learning. The traditional techniques for detecting these defects consist of manual inspection of manufactured parts, image processing methods such as infrared imaging. But manual inspection and other non-destructive defect detection technologies tend to be error-prone, time and manpower-consuming at the same time. To overcome these obstacles with the advances of recent technologies machine learning defect detection has emerged as a technology that uses advanced equipment and deep learning methods to conduct in-process and post-process imaging for defect identification. So the sole purpose of our dissertation is to incorporate this idea of utilizing machine learning methods to detect and classify different manufacturing defects such as lack of fusion, gas porosity, cracks including good quality parts using optical images. Among different machine learning (ML) algorithms available, random forest, k nearest neighbor, and anomaly detection machine learning algorithm can be used to classify, cluster, and detect anomalies in different types of infill defects found in AM parts [16]. These methods can also help in CyberManufacturing systems (CMS) for sustainable manufacturing [17]. CNN is one of the widely accepted artificial neural network (ANN) methods for image processing, segmentation, feature extraction, and pattern recognition

Deep learning is a type of machine learning and artificial intelligence (AI) that imitates the way humans gain certain types of knowledge. Deep learning is an important element of data science, which includes statistics and predictive modeling. It is extremely beneficial to data scientists who are tasked with collecting, analyzing, and interpreting large amounts of data; deep learning makes this process faster and easier. Deep learning uses multiple convolutional layers structured inside a neural network where input data characteristics are learned to process lower-level features into more abstract high-level features. These features are then used to classify data into categories learned from the training process. The results are expressed in the form of vectors, feature maps, etc. Based on the powerful learning ability and feature extraction of deep learning, many researchers have used this technology to detect defects and improve overall detection efficiency and quality.

Recently Convolutional neural network has been proved as one of the most popular deep learning methods used as the defect detection mechanism [18, 19, 20, 21, 22, 23, 24, 25, 26, 27]. The use of convolutional neural networks (CNNs) for defect detection can be summarized in two major scenarios. The first one consists of designing a complex, multi-layer CNN structure, then obtaining image features from a different network to finally perform image defect detection based on end-to-end training. In contrast, the second one combines the CNN with a Conditional Random Field (CRF) model, and either uses CRF energy functions as a constraint to train the CNN or optimizes network prediction results to conduct defect detection [28]. Essentially, these convolution layers promote weight sharing to examine pixels in kernels and develop visual context to classify images.

Unlike Neural Network (NN) where the weights are independent, CNN's weights are attached to the neighboring pixels to extract features in every part of the image.CNN uses max pooling to replace output with a max summary to reduce data size and processing time. This allows us to determine features that produce the highest impact and reduce the risk of overfitting. Max pooling takes two hyperparameters named stride and size. The stride will determine the skip of value pools while the size will determine how big the value pools are in every skip. After each convolutional and max-pooling operation, we apply Rectified Linear Unit (ReLU). The ReLU function mimics neuron activations on a "big enough stimulus" to introduce non linearity for values x>0 and returns 0 if it does not meet the condition [28]. This method has been effective to solve diminishing gradients. Weights that are very small will remain as 0 after the ReLU activation function. Finally,the convolutional and max-pooling feature map outputs will be served with a Fully Connected Layer (FCL). Then the feature outputs is flattened to a column vector and feed-forward it to FCL. After that features are wrapped with a softmax activation function which assigns decimal probabilities for each possible label that add up to 1 to 0. In order to keep the output size of each kernel consistent with the input, padding and striding were used. To fully cover the filters ($F \times F$) for all convolutional layers, the same padding and striding were used according to Equation 1,

$$P = \frac{F - 1}{2} \quad \text{and} \quad S = 1 \tag{1.1}$$

where, P, S, and F are padding, striding, and filter size, respectively. The output size for convolutional (W_c) and pooling (W_p) layers were obtained using Equations 2 and 3, respectively,

$$W_c = \frac{W_p - F + 2P}{S} + 1 \tag{1.2}$$

$$W_p = \frac{W_c - F}{S} + 1 \tag{1.3}$$

where, W_c and W_p are the convolutional and polling layer output sizes, respectively. Finally, the values of the last pooling layer were concatenated into a vector. Every node in the previous layer is connected to the last layer and represents which distinct label to output. In general, the advantages of CNNs include the network's strong ability to learn high-dimensional data in addition to abstract, essential, and high-level features from the input data.

In this work, we utilized raw optical images from previous work where Wen et al. demonstrated a successful implementation of CNN architecture in metal additive manufacturing part inspection [1]. Though they achieved 92% overall accuracy for their dataset, proper dataset balancing, data augmentation, parameter tuning, and CNN architecture settings including input size, kernel size, feature extraction and classification layers can improve the performance of deep learning models in detecting defects for AM parts [29, 30, 31, 32, 33, 34, 35, 36]. We implemented data balancing using the upsampling and oversampling techniques. On the fly, data augmentation has also been demonstrated on the data set to observe their individual impact on the performance of the CNN network. Hyperparameter tuning, dropout, and regularization techniques were also included. Later, we performed experimentation on the different architectural settings for the CNN network to obtain optimized results and compared the results between them and the results from the previous study.

PAPER

I. A CONVOLUTIONAL NEURAL NETWORK (CNN) FOR DEFECT DETECTION OF ADDITIVELY MANUFACTURED PARTS

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ABSTRACT

Additive manufacturing (AM), fundamentally different from traditional subtractive manufacturing techniques, is a layer-by-layer deposition process to fabricate parts with complex geometries. The formation of defects within AM components is a major concern for critical structural and cyclic loading applications. Understanding the mechanisms of defect formation and identifying the defects play an important role in improving the product lifecycle. While convolutional neural network (CNN) has already been demonstrated to be an effective deep learning tool for automated detection of defects for both conventional and AM processes, a network with optimized parameters including proper data processing and sampling can improve the performance of the architecture. In this study, for the detection of good deposition quality and defects such as lack of fusion, gas porosity, and cracks in a fusion-based AM process, a CNN architecture is presented comparing the classification report and evaluation of different architectural settings and obtaining the optimized result from them. The performance of the network was also compared with the results from the previous study. The overall accuracy (98%) for both training and testing the CNN network presented in this work transcends the current state of the art (92%) for AM defect detection.

Keywords: Additive manufacturing; convolutional neural network; deep learning; defect detection; lack of fusion; gas porosity

1. INTRODUCTION

Additive manufacturing/3D printing has gained much attention to research and application fields such as defense, maritime, aerospace, space research, automotive, medical, agriculture, biomedical, electronics, energy, oil, gas industries, etc [1, 2, 3, 4, 5, 6, 7]. Among different additive manufacturing (AM) processes available, laser aided direct energy deposition, selective laser melting, and wire arc deposition process are the most widely used techniques for metal additive manufacturing [8, 9, 10, 11]. AM processes for metals have several advantages over the traditional manufacturing processes i.e. producing near net-shaped geometries, manufacturing parts with complex geometries, fabricating components with custom designed shapes, low consumption of raw materials, depositing functionally graded materials, metal composites, and alloys. But the parts manufactured with AM processes are comprised of a lot of different types of defects such as balling, spattering, keyholing, lack of fusion, gas porosity, voids, microcracks, etc [12, 13, 14, 15, 16]. The formation of defects in AM process depends on the feedstock characteristics, process types and environment, and fabrication process parameters. Low energy input into the melt pool results in unmelted or partially melted particles that create the lack of fusion type defects while high energy input originates balling, spattering, keyholing, and cracks. Gas porosity is impregnated into the deposited parts due to the inert environment used in AM process and gas entrapment into the feedstock during the raw material manufacturing process. Voids are generated into AM parts because of the vaporization of the contaminants and particles with low melting temperature present into the feedstock. All these defects significantly influence both the static and dynamic mechanical properties of the material such as tensile, toughness, hardness, fatigue, corrosion, etc [17, 18, 19, 20, 21]. The mechanical properties of the material can be improved by eliminating severe defects critical to any specific application and minimizing the population and size of other defects. Selecting top-quality feedstock and proper AM processing technique including the environment, and optimizing process parameters and tool path, the number of defects can be mitigated, but the presence of defects cannot be ignored completely. Therefore, for application-specific inspection and qualification of parts manufactured using AM process, identification and classification of the types of defects are very important. Since the manual inspection is error-prone and tedious work, therefore, we proposed an offline neural network-based deep learning architecture called convolutional neural network (CNN) to detect and classify the defects present in the AM parts. In this study, we endeavored to identify good quality deposition, lack of fusion, gas porosity, and crack type defects using optical images since such defects are most commonly found in AM parts.

Deep learning is an artificial intelligence (AI) system allowing machines or computers to make predictions and decisions automatically using data-driven modeling approaches. AI has demonstrated to be an effective tool to implement in manufacturing field specially AM and its defect detection. Among different machine learning (ML) algorithms available, random forest, k nearest neighbor, and anomaly detection machine learning algorithm can be used to classify, cluster, and detect anomalies in different types of infill defects found in AM parts [22]. These methods can also help in CyberManufacturing systems (CMS) for sustainable manufacturing [23]. CNN is one of the widely accepted artificial neural network (ANN) methods for image processing, segmentation, feature extraction, and pattern recognition. Among different supervised machine learning techniques, CNN is a very popular method applied in different fields including both additive and subtractive manufacturing processes for defect detection [24, 25, 26, 27, 28, 29, 30, 31, 32, 33]. Zhang et al. used deep CNN to detect defects in fabrics [34]. Ouyang et al. implemented different activation layer embedded CNN to detect defects in fabrics for quality assurance and compared the performance of Sigmoid, Tanh, ReLU (rectified linear unit), and PPAL (pairwise potential activation layer) activation functions at 10^{-4} and 10^{-10} learning rates [35]. Jing et al. pretrained their deep CNN model with MNIST dataset and then applied the model to detect defects in fabrics [36]. Garg et al. applied the deep CNN approach for the defect detection of textured surfaces [37]. Wang et al. proposed a fast CNN defect detection model extracting powerful features with less prior knowledge in product quality control using optical images from the DAGM dataset provided by DAGM (German Association for Pattern Recognition) and GNNS (German Chapter of the European Neural Network Society) [38]. The model was also robust to noise. Chen et al. introduced cascaded CNN to detect defects of fasteners used on the catenary support device [39]. Several studies have been conducted recently to detect welding defects [40, 41, 42, 43, 44, 45, 46]. Guo et al. used CNN for resistance welding spot defect detection and achieved 99.0% accuracy on test images [47]. Different deep CNN models have also been proposed by different researchers for the defect detection of different casting materials [48, 49]. Lin et al. used X-ray digital images for the deep CNN model to detect casting defects [48]. The CNN models are not only limited to traditional manufacturing processes but also have been applied for AM part quality inspection. eher. Though they achieved 92% overall accuracy for their dataset, proper dataset balancing, data augmentation, parameter tuning, and CNN architecture settings including input size, kernel size, feature extraction and classification layers can improve the performance of deep learning models in detecting defects for AM parts [50, 51, 52, 53, 54, 55, 56, 57].

In this study, we used raw optical images and processed them to prepare the dataset. We also balanced the training data using upsampling/oversampling technique and then implemented on the fly data augmentation to demonstrate the effect of proper data sampling and augmentation on the improvement of the performance of a simple CNN architecture. Hyperparameter tuning, dropout, and regularization techniques were also included. Later, we performed experimentation on the different architectural settings for the CNN network to obtain optimized results and compared the results between them and the results from the previous study.

2. DATA COLLECTION AND PROCESSING

For data preparation and sampling, raw optical images were collected from the previous study [58]. The images captured by a Hirox (Hackensack, NJ, USA) digital microscope contain the traverse cross-section of different laser metal deposited (LMD) materials i.e. AISI 304 and 316 stainless steel, Inconel 718 alloys, AlCoCrFeNi alloys, and Ti-6Al-4V. The raw images had a resolution of 1600×1200 pixels including the epoxy as the background. We sliced the images from left to right and top to bottom with 150 pixels increments to obtain images of 400×400 pixels. Following the process, 135 raw images result in 7290 total images in which 4944 and 2346 images were useful and background, respectively. Later, the useful images were divided into four classes by labeling them manually as the good quality, lack of fusion, gas porosity, and cracks. The visualization of the sample images from each class is shown in Figure 1. After preparing the dataset, 80% and 20% data from each class were distributed randomly for training and testing the network, respectively, while 20% of the training data was used for validation purposes. The distribution of the dataset for training, validation, and testing is shown in Figure 2. This particular dataset turned out to be heavily imbalanced especially for the defects as shown in the bar chart. Previous studies show that constructing a classifier with imbalanced data biases the modeled network to be more inclined toward the majority class present in the dataset. Therefore, data balancing is very crucial in this study. Several studies have addressed the imbalance class label issues and proposed possible solutions to these problems. Alejo et al. [50] presented a solution of handling imbalanced output class labels for pattern recognition using resampling the original dataset either upsampling the minority classes or undersampling the majority class labels. Dubey et al.[59] applied

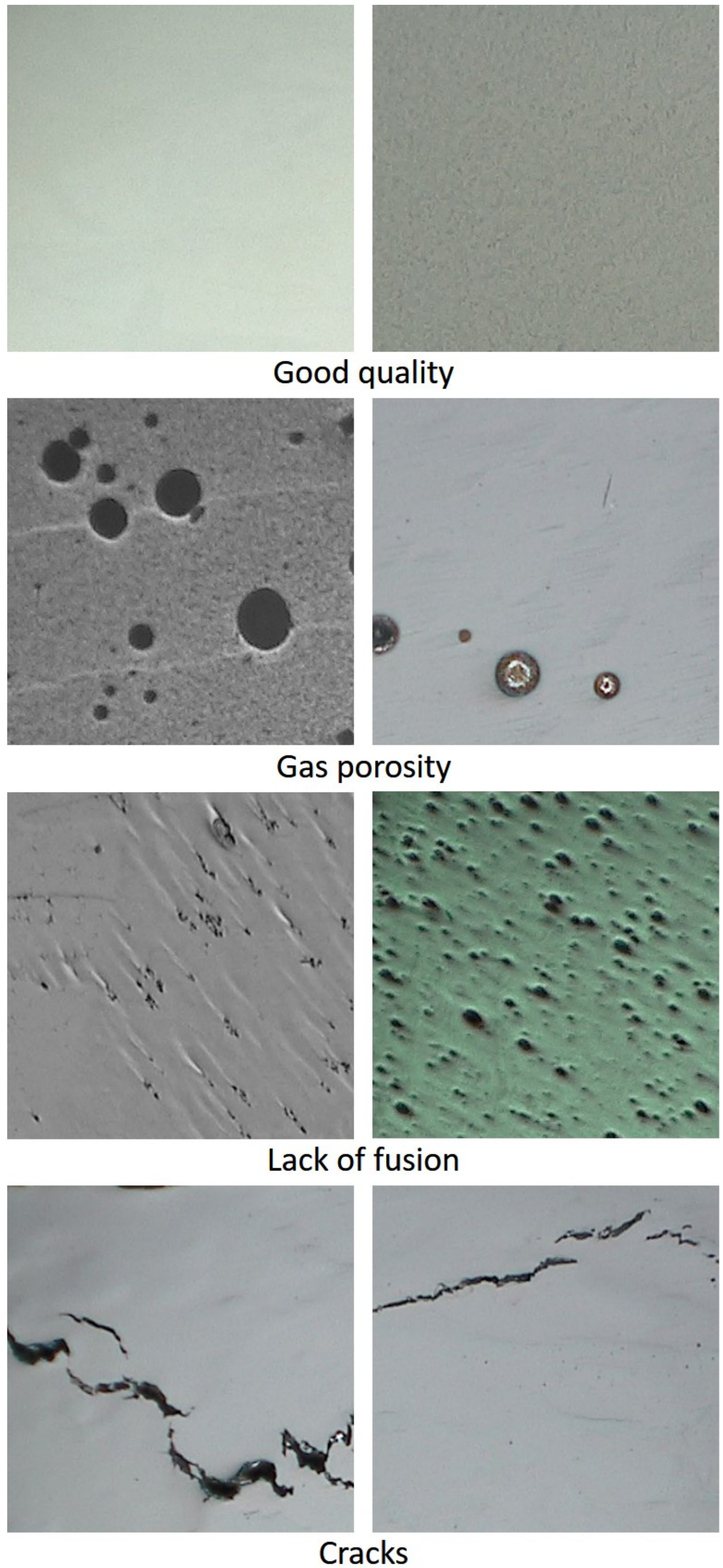

Figure 1. SAMPLE IMAGES OF GOOD QUALITY DEPOSITION AND DEFECTS.

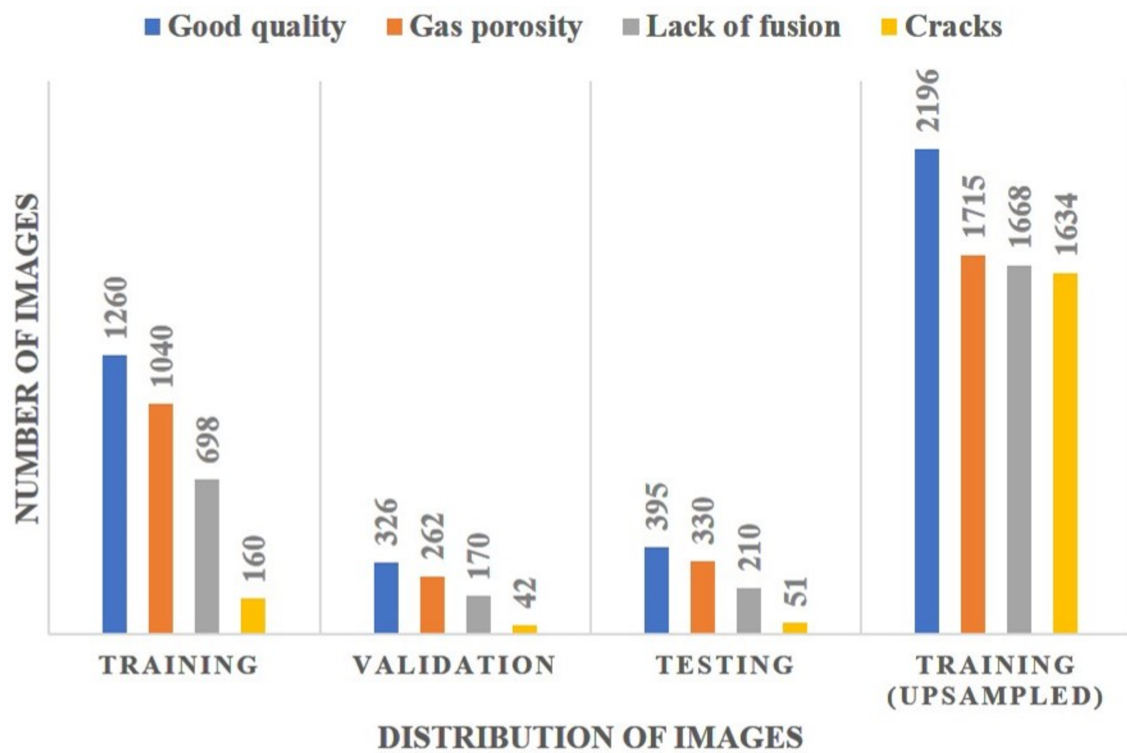

Figure 2. DISTRIBUTION OF THE DATASET FOR TRAINING, VALIDATION, AND TESTING.

random undersampling and oversampling for neuron imaging classification. The sampling process is usually applied to the training data only. In this present work, while distributing the dataset in a ratio for training and testing, both the training and testing samples were not symmetrically distributed among the target defect classes. To address this issue, we utilized upsampling technique. We randomly upsampled all the class types to balance the dataset for training purposes only. The training data after upsampling is shown in Figure 2. The upsampling technique also helps to improve the performance of the CNN model by increasing the number of total input images.

3. EXPERIMENTAL SETTING AND PROCEDURE

A CNN model consists of two parts. First, a model with multiple convolutional layers is designed to extract the features from an image and then multiple layers of perceptron (MLP) with dense layers are constructed for classification purposes. In this section, the design of the CNN architecture with the experimental procedure is described.

3.1. FEATURE EXTRACTION MODEL

The performance of a CNN model in classification problems for a specific dataset depends on the input size, the number of inputs, and how balanced the dataset is. Additionally, the number of convolutional layers, kernel size, and numbers in each convolutional layer, padding, and striding procedure, overfitting reduction methods, and the fully dense layers used for classifiers significantly influence the overall outcome of the model. In this study, we first constructed a simple CNN model following the model used in the previous study [58] to demonstrate the effect of data balancing and augmentation on the performance of the model. Then we experimented with different CNN architectures varying the input size to obtain the optimal settings of the architecture to acquire the best output from them. The final CNN model used in this study is shown in Figure 3. The architecture has two blocks. The first block is for feature extraction from the optical images while the other one is for the classification of the defined defects. The feature extraction layers fundamentally consist of convolutional layers with linear and nonlinear operations, i.e., convolution operation and activation function. In the first layer, the mathematical operation of convolution was performed between the input image of $224 \times 224 \times 3$ pixel and 32 filters of kernel size 3×3. By sliding the filter over the input image, the dot product of the filters and the parts of the input image with respect to the kernel size was calculated. The output was considered as the feature map that gives us information about the image such as the corners and edges. Later, the output of the first feature map layer was normalized with ReLU activation function to

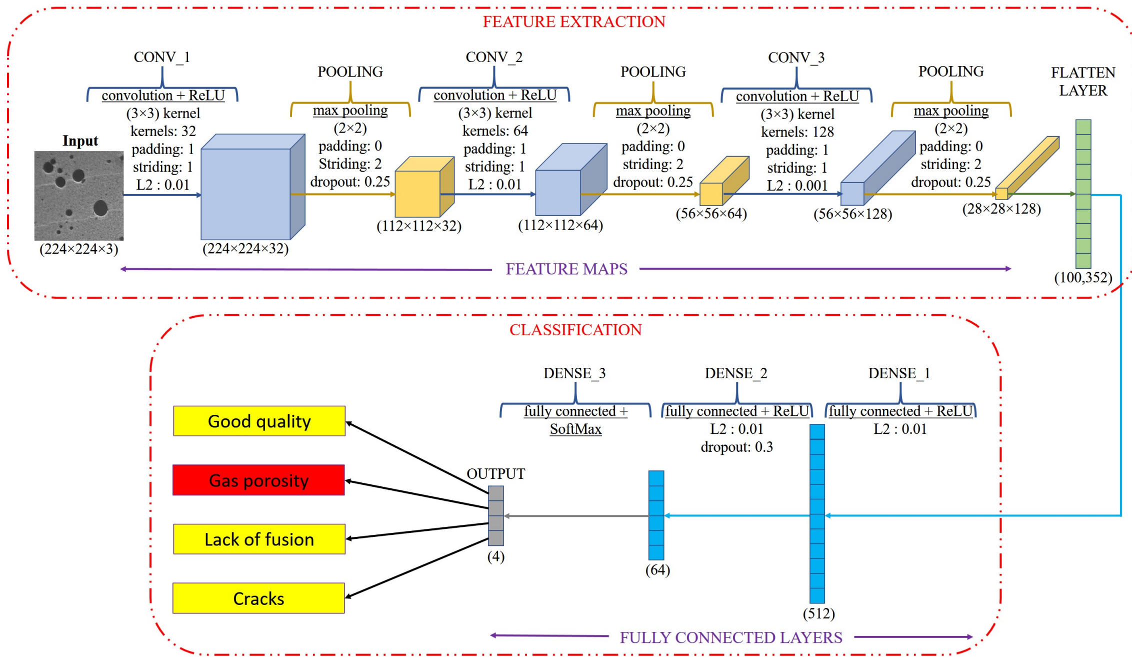

Figure 3. FINAL CNN ARCHITECTURAL SETTING AND PARAMETERS FOR THE DEFECT DETECTION OF AM PARTS.

learn and approximate any kind of continuous and complex relationship between variables of the network. Then the rectified linear output of the layer was resized using the pooling layer. The max-pooling operation was utilized in this work. This operation selects the maximum element from the region of the feature map covered by the filter. The output after the max-pooling layer becomes a feature map containing the most prominent features of the previous feature map. To reduce the number of learning parameters and the amount of computation, we used (2×2) pool size. The output of the pooling layer was fed to the next convolutional layer to learn several other features of the input image. Our feature extraction architecture consists of three convolutional layers of 32, 64, and 128 filters with kernel size (3×3) and pooling layers. In order to keep the output size of each kernel consistent with the input, padding and striding were used. The default setting of striding 1 and 2 was applied for convolutional and pooling layers, respectively. To fully cover the filters $(F \times F)$ for all convolutional layers, the same padding and striding were used according to Equation 1,

$$P = \frac{F - 1}{2} \quad \text{and} \quad S = 1 \tag{1}$$

where, P, S, and F are padding, striding, and filter size, respectively. The output size for convolutional (W_c) and pooling (W_p) layers were obtained using Equations 2 and 3, respectively,

$$W_c = \frac{W_p - F + 2P}{S} + 1 \tag{2}$$

$$W_p = \frac{W_c - F}{S} + 1 \tag{3}$$

where, W_c and W_p are the convolutional and polling layer output sizes, respectively. Finally, the values of the last pooling layer were concatenated into a vector. The flattened layer (shown in Figure 3) was the output of the feature extraction model and input to the classification model.

3.2. CLASSIFICATION MODEL

The classification model of the architecture shown in Figure 3 consists of one output layer followed by two fully connected layers of size 512 and 64. The flattened values of the feature extraction model pass through these two layers. The number of elements in the output layer was equal to the number of classes according to the problem definition. While ReLU was used as the activation function for fully dense layers, the activation function for the final output layer was SoftMax. For a multi-class classifier, SoftMax normalizes the output values from the last fully connected layer to target class probabilities, where each value ranges between 0 and 1 and all values sum to 1.

3.3. OVERFITTING MINIMIZATION

One of the main challenges that arise in any machine learning algorithm is an overfitting issue. Overfitting refers to a situation where a model learns the regularities of the training dataset which includes memorizing all the irrelevant noise of the model, not the signal, and thus works very poorly to newly introduced data. To reduce this problem, we initially used up-sampling to introduce a larger training data point for the network as mentioned earlier. But there still remain chances of constructing an overfitted model with expanded training dataset. Therefore, to minimize overfitting, we utilized solutions such as regularization with dropout or weight decay process and data augmentation for this work-frame. Dropout is a technique where randomly selected neurons are ignored during training. They are dropped out randomly. This means that their contribution to the activation of downstream neurons is temporally removed on the forward pass and any weight updates are not applied to the neuron on the backward pass. Weight decay referred to as L2 regularization also called Ridge-regression or Euclidean norm, reduces overfitting by penalizing the model's weights so that the weights take only small values. In this study, while L2 regularization was used for all the convolutional and fully dense layers, dropout was implemented for pooling layers and second dense layers only.

3.4. DATA AUGMENTATION

Besides implementing all the above-mentioned techniques to reduce the overfitting, we also applied data augmentation on our training dataset only to create an improved and generalized model for all prospects. In this process, different data transforming criteria were applied to the training data so that the model does not get a similar type of inputs throughout the training iterations. Among various data transformations techniques, we applied 45° rotation, 15° shifting of both height and width with a horizontal flipping to all the training sets. Zooming the image was avoided since the spatial information of the defect can be at any location of the image in this data frame. The data augmentation was implemented on the fly while training the architecture.

3.5. TRAINING DETAILS

The architectural setting and network experiments in this work were performed on a 12 core Advanced Micro device (AMD) Ryzen threadripper 1920x processor with a GeForce 1080Ti graphics processing unit (GPU). Code for the CNN was developed on python 3.6.9 using TensorFlow (version 1.14). Throughout the different experimental settings, some training parameters were kept constant. Such as, or the optimization algorithm, Adam was utilized, which is an extension of the stochastic gradient descent algorithm. Categorical cross-entropy was used as the loss function for this multi-class classification problem. A batch size of 20 and a learning rate 10^{-3} were employed for training the network. The network was trained for 300 epochs with 350 and 80 steps per epoch for the training and validation, respectively.

4. RESULTS AND ANALYSIS

In this study, we experimented with different CNN architectural settings to obtain the optimal results for the defect detection of AM parts i.e. AlCoCrFeNi alloy, Ti-6Al-4V, and AISI 304 stainless steel. The features were extracted randomly from the pool of different parts randomly. While the feature extraction mapping model remained the same in all experiments, the input size, sampling, data augmentation, and classification block were varied to achieve minimal overfitting and a good correlation between the loss and accuracy for training, validation, and testing the models. Figure 4 shows the loss and accuracy for both the training and validation of different configurations while training the models.

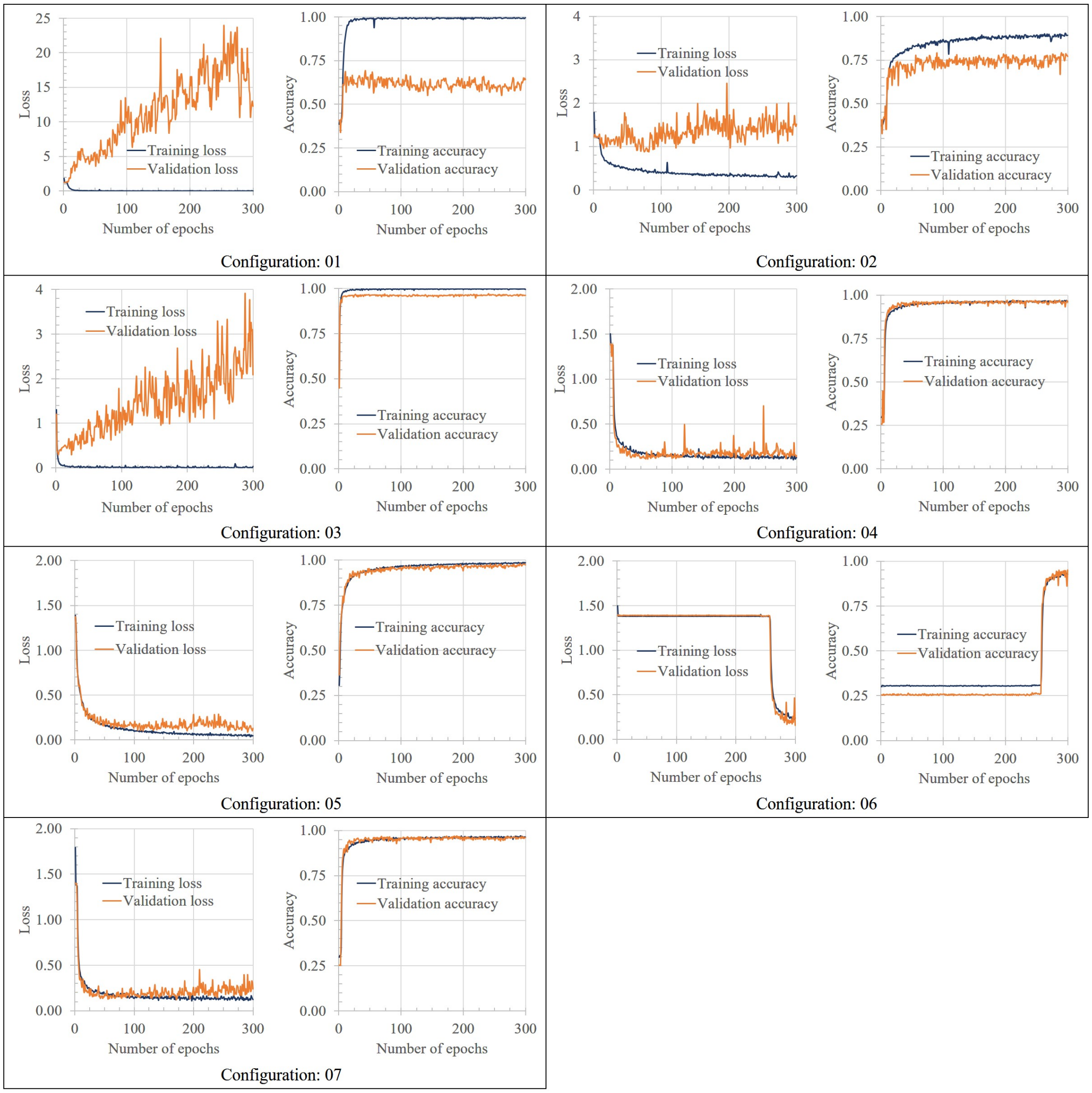

Figure 4. TRAINING AND VALIDATION RESULTS FOR DIFFERENT ARCHITECTURAL SETTINGS PRESENTED IN TABLE 1.

The different model configurations and settings used in this work and their final loss and accuracy for training, validation, testing are presented in Table 1. In configuration #1, we trained our model with sampled data only. No upsampling and augmentation were applied. The objective of training our model with such configuration was to observe the behavior of the CNN model without any additional sampling and augmentation. As we can

Table 1. CNN MODEL CONFIGURATIONS AND SETTINGS WITH TRAINING, VALIDATION, AND TESTING RESULTS.

CFG	Input	Upsampling	Augmentation	Classifier	Loss			Accuracy		
					Training	Validation	Testing	Training	Validation	Testing
1	$224 \times 224 \times 3$	✗	✗	512	0.01	8.59	2.11	0.995	0.650	0.866
2		✗	✓	512	0.32	1.52	0.31	0.893	0.771	0.943
3		✓	✗	512	0.03	2.08	1.14	0.996	0.963	0.963
4		✓	✓	512	0.15	0.13	0.09	0.965	0.959	0.975
5		✓	✓	512, 64	0.04	0.18	0.08	0.984	0.972	0.976
6	$200 \times 200 \times 3$	✓	✓	512, 64	0.24	0.15	0.22	0.926	0.952	0.928
7	$256 \times 256 \times 3$	✓	✓	512, 64	0.12	0.24	0.11	0.962	0.962	0.968
Final	$224 \times 224 \times 3$	✓	✓	512, 64	0.05	0.10	0.13	0.98	0.98	0.98

see, the training loss went to almost zero but the validation loss was too high. Though we implemented L2 regularization and drop out in our model to reduce overfitting, the loss for training and validation depicts that the model is overfitted. The accuracy of the model for both the training and testing also demonstrates the overfitting nature of the model. In order to minimize the overfitting, we included on the fly data augmentation along with dropout and regularization in configuration #2.

As we can see from the Figure 4 for configuration #2, the discrepancy for both the loss and accuracy between the training and validation was minimized to some extent because of applying data augmentation. Later, in configuration #3, we experimented with the influence of upsampling the training data only on the performance of the model. Though the training and validation accuracy in configuration #3 was in good agreement compared to the accuracy for both the configuration #1 and #2, the difference of loss between the training and validation was less compared to the difference we had in configuration #1 but it was much higher than configuration #2. The higher accuracy for both the training and validation may be due to the fewer data present in the validation process. The analysis of the results obtained from configuration #2 and #3 indicates that the combined effect of the upsampling and data augmentation process can minimize the difference of both loss and accuracy between training and validation which is obvious from the configuration #4 in Figure 4. The summary of the experimentation for configuration #1 to #4 depicts that dropout and regularization can not alone improve the performance of a CNN model for defect detection, upsampling and data augmentation also need to be considered for an imbalanced dataset.

The objective of this study was to find an optimal configuration for the improved performance of the CNN model. In configuration #4, both the upsampling and data augmentation were applied for the training dataset while a single fully dense layer of 512 neurons was used. Therefore, we increased the number of layers in the classification block and trained the network to observe the influence of the additional layer on the model performance. While comparing the results of the configuration #4 and #5, the plot of the loss and accuracy for configuration #4 shows that for training and validation both the loss and accuracy converges much earlier than what we see in configuration #5. The possible reason for this may be the number of total trainable parameters in configuration #5 is more than the parameters in configuration #4. We can also see that the validation loss has some spikes in configuration #4 during training the network while the validation loss in configuration #5 converges smoothly compared to configuration #4. The combined training, validation, and testing losses for both configuration #4 and #5 do not have any significant differences, but the configuration #5 has improved accuracy for training, validation, and testing while compared with configuration #4. Therefore, we can conclude that configuration #5 is the optimal CNN model for the $224 \times 224 \times 3$ input size.

For further investigation, we changed the input size for the model in configuration #5. $200 \times 200 \times 3$ and $256 \times 256 \times 3$ input size were used for configuration #6 and #7, respectively. As we can see from the plot of loss and accuracy for configuration #6, the loss for both training and validation remained flat up to 250 epochs. After that, the model started getting trained smoothly. The possible reason for such behavior is unknown. But the overall accuracy of the model dropped compared to other configurations. For configuration #7, the loss and accuracy are also less compared to configuration #5. The total time needed for the training was approximately 9 hours for the configurations #5, #6, and #7 experimented in this work frame. The testing set took around 5 minutes to generate all the testing dataset results. We can conclude that configuration #5 yields the best result for loss and accuracy of training, validation, testing. But in this configuration, the loss and accuracy for both training and validation were not flattened after 300 epochs. Therefore, further training was needed. We trained the model for additional 100 epochs with a 10^{-4} learning rate. Since the model was pretrained with a 10^{-3} learning rate, the learning rate for further training was reduced. The final training and validation accuracy achieved was 98.5% and 98.4%, respectively while the losses were 0.045 and 0.103 for training and validation, respectively. The final testing accuracy and loss were 97.9% and 0.128, respectively. Previous study [58] on the defect detection reported an accuracy of 92.1%. Comparing the results from the previous study, we achieved a 6% improvement in defect detection of AM parts using optical images. Additionally, the kernel size used in the previous study was 5×5, while in our study we used 3×3. Smaller kernel size takes less time in processing the data. In our study, we used RGB images as input while gray-scale images was used in previous study. We assume this to be another reason for getting better results.

From the above discussion, this is obvious that the configuration #5 for the CNN model gives the best results in terms of training, validation, and testing. Finally, the performance of the optimized CNN model was evaluated using precision, recall, and $\mathrm{F}_{\mathrm{score}}$.

$$Precision = \frac{TP}{TP + FP} \tag{4}$$

$$Recall = \frac{TP}{FN + TP} \tag{5}$$

$$F_{score} = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{6}$$

According to Equation 4 and 5, precision is defined as the ratio of true positive (TP) and the sum of the true positive (TP) and false positive (FP) results, while recall is the ratio of the true positive (TP) and the sum of the false negative (FN) and true positive (TP) results. In Equation 6, F_{score} represents the overall performance of the precision and recall. The precision, recall, and the F_{score} of the optimized CNN model is presented in Table 2 with the comparison of previous study. The precision (>= 0.97) and recall (>= 0.97) for each class type are in good agreement with the accuracy for the training, validation, and testing. While a scatter is seen in the previous study, the results from the evaluation metrics for the current study including the F_{score} (>= 0.97) reflect that the CNN model is well trained with minimal overfitting and high accuracy. Table 3 represents the comparison of the CNN architecture and parameters used in this study and previous study [58]. Notable differences can be seen in the input image size, number of images, CNN kernels, learning rates, and epochs in both

Table 2. COMPARISON OF THE PERFORMANCE EVALUATION METRICS OF FINAL CNN MODEL (CONFIGURATION #5) IN THIS STUDY AND PREVIOUS STUDY [58].

Comparison	**This study**			**Previous study**		
Classes	**Precision**	**Recall**	**F_{score}**	**Precision**	**Recall**	**F_{score}**
Good quality	0.99	0.98	0.98	0.96	0.94	0.95
Gas porosity	0.98	0.97	0.97	0.91	0.87	0.89
Lack of fusion	0.97	0.99	0.98	0.88	0.92	0.90
Cracks	0.98	0.98	0.98	0.94	0.95	0.95
Average						
Macro average	0.98	0.98	0.98	not given		
Weighted average	0.98	0.98	0.98	not given		
Accuracy	**0.98**			**0.92**		

Table 3. COMPARISON OF CNN ARCHITECTURE AND PARAMETERS USED IN THIS STUDY AND PREVIOUS STUDY [58].

Parameters	**Input image**	**Input size**	**Total images**	**Data augment**	**CNN kernels**	**Striding**
This study	RGB	$224 \times 224 \times 3$	8,199	Rotation: 45° Shifting: height and width Flipping: horizontal	CONV 1: $3 \times 3 \times 32$ CONV 2: $3 \times 3 \times 64$ CONV 3: $3 \times 3 \times 128$	CONV all: 1 Pooling all: 2
Previous study	Grey	$224 \times 224 \times 1$	4,140	Rotation: not given Flipping: horizontal Cropping: random Noise and blur: Gaussian	CONV 1: $5 \times 5 \times 32$ CONV 2: $5 \times 5 \times 64$ CONV 3: $5 \times 5 \times 128$	CONV all: 1 Pooling all: 1
Parameters	**Padding**	**Dropout**	**Regularization**	**Learning rate**	**Epochs**	**Training time**
This study	CONV all: 1 Pooling all: 1	Pooling all: 0.25 Dense all: 0.3	CONV 1 and 2: 0.01 CONV 3: 0.001 Dense all: 0.01	1×10^{-3} 1×10^{-4}	300 100	9:10:38
Previous study	not given	Pooling all: 0.25 Dense all: 0.25	CONV all: 1×10^{-5} Dense all: 1×10^{-5}	1×10^{-4}	300	1:46:32

studies. All these parameters including the network architecture play a significant role in achieving 98% from 92% performance of the CNN architecture for defect detection of AM parts.

5. CONCLUSION

In this paper, additive manufacturing part defects were detected from optical images using a convolutional neural network (CNN) based artificial intelligence model. We presented a systematic approach for data preparation and processing. The effect of data balancing using upsampling and training the network with data augmentation on the performance of the CNN model was also evaluated. We experimented with different architectural settings in this study and proposed a CNN model with optimal parameters that obtain an accuracy above 97% for all the classes while training, validating, and testing the model. The performance of the proposed CNN model in this study surpasses the results (92%)

reported in the previous study. While a classification model was developed in this work, the future work includes multiple defects detection, localization, and segmentation using different object-detecting CNN models.

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SECTION

2. CONCLUSION AND FUTURE WORK

In this work, our motivation was to exhibit a smart defect detection mechanism based on a deep learning algorithm for the most prominent defects such as cracks, lack of fusion, gas porosity with good quality parts occurring in an additive manufacturing process. Convolutional neural network-based artificial intelligence system utilized a data set of optical images of additively manufactured parts to establish this defect detection system. Appropriate data preparation and processing were also implemented beforehand for the proper execution of the network setting. Different CNN architectural settings were experimented with different hyperparameter setting observing their impact on the obtained result of the network performance. Our optimal network setting achieved a total accuracy of 97 percent on the training, testing, and validation sets. This result also suppresses the performance of the previous study which was recorded as 92 percent. Overall, in this work, we achieved our desired goal of making a more precise, optimized, and accurate defect detection CNN network for the most frequently occuring defects such as cracks, gas porosity, lack of fusion in any AM manufacturing process also with the appropriate identification of good quality parts. While our concentration was completely on the construction of an optimized defect detection network setting for this work multiple defect identification using real-time object detection system, segmentation network for proper localization of the defined defects can be considered as an extended future work of this work.

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VITA

Musarrat Farzana Rahman was born in Bangladesh, a small south Asian country marked by lush greenery and many waterways. She completed her graduation with a Bachelor of Science in Electrical and Electronic Engineering from Khulna University of Engineering and Technology, Bangladesh in June 2016. After graduation, she joined Edotco Bangladesh Co. as a support engineer core in Dhaka, Bangladesh. She worked for about 1.5 years in the maintenance of the core system under the energy management department of the Edotco group.

In 2020, she joined LAMP (Laser Aided Manufacturing Process) lab under the supervision of Dr. Frank Liou at Missouri University of Science and technology for M.Sc in Manufacturing Engineering. During her time as the graduate research assistant in the lab, she studied machine learning and artificial intelligence incorporation with the growing technology of additive manufacturing. She mainly worked on the development of an effective, fast, and accurate defect detecting mechanism using deep learning for additively manufactured parts.

In her personal life, she enjoyed traveling, roaming around nature, and capturing the moments of life through lenses.

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