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ORIGINAL RESEARCH

Ensemble learning based defect detection of laser sintering

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Abstract

In rapid development, Selective Laser Sintering (SLS) creates prototypes by processing industrial materials, for example, polymers. Such materials are usually in powder form and fused by a laser beam. The manufacturing quality depends on the interaction between a high-energy laser beam and the powdered material. However, in-homogeneous temperature distribution, unstable laser powder, and inconsistent powder densities can cause defects in the final product, for example, Powder Bed Defects. Such factors can lead to irregularities, for example, warping, distortion, and inadequate powder bed fusion. These irregularities may affect the profitable SLS production. Consequently, detecting powder bed defects requires automation. An ensemble learning-based approach is proposed for detecting defects in SLS powder bed images from this perceptive. The proposed approach first pre-processes the images to reduce the computational complexity. Then, the Convolutional Neural Network (CNN) based ensembled models (off-the-shelf CNN, bagged CNN, and boosted CNN) are implemented and compared. The ensemble learning CNN (bagged and boosted CNN) is good for powder bed detection. The evaluation results indicate that the performance of bagged CNN is significant. It also indicates that preprocessing of the images, mainly cropping to the region of interest, improves the performance of the proposed approach. The training and testing accuracy of the bagged CNN is 96.1% and 95.1%, respectively.

KEYWORDS

laser beam effects, laser beams

1 | INTRODUCTION

Selective Laser Sintering (SLS) is a rapidly growing technique for prototyping and additive manufacturing (also known as 'Rapid Manufacturing') [1, 2]. The main advantage of SLS is that it can process most of the commonly used industrial materials, for example, polymers [3]. However, the process of SLS uses different polymers, that is, polyamides, polystyrene, thermoplastic elastomers, and polypropylene with their variants [4]. Such material is provided in powdered form, which is fused by a high-energy source, for example, a laser beam. The fusion creates complex three-dimensional shapes guided by Computer-Aided Design (CAD). Moreover, SLS has a significant advantage over traditional manufacturing because of its ability to create complex three-dimensional objects [5].

The manufacturing quality depends on the interaction between a high-energy laser beam and the powdered material. This process of fusion and solidification of powdered material produces high-quality parts. Good and reproducible quality parts can be created by implementing a reliable and automated production process and quality control [6]. Moreover, the quality of SLS production depends on the fusion of powdered material, powder bed, and powder spreading [7, 8]. Many technical complexities can cause defects in the final product, for example, Powder Bed Defects (PBDs), in-homogeneous temperature distribution, unstable laser powder, and inconsistent powder densities [9]. These factors can lead to many irregularities in powder beds, that is, spatter [10], warping [11], distortion [12], and inadequate powder bed fusion [13].

Quality production is very critical to achieving profitable SLS production. The above-mentioned defects can lead to bad quality products, material waste, and additional costs [9]. Consequently, detecting the powder bed defects in the SLS process is critical for SLS production.

Machine/Deep Learning (M/DL) algorithms are commonly implemented for the automatic detection and monitoring of defects in SLS powder beds [9, 14, 15]. Such algorithms acquire the pre-processed high-quality images of powder beds. The conventional ML algorithms, that is, decision tree, linear regression, and support vector machine, are limited to processing raw unstructured data (images) [16]. Consequently, DL algorithms, especially ensemble learning are better in this scope and can provide the solution to the said problem in an effective manner [17]. Ensemble learning algorithms combine multiple DL models to reduce the error by compensation. As a result, the overall prediction performance could be increased [18].

From this perceptive, this paper proposes an ensemble learning-based approach for defect detection for SLS powder bed images (called 'ELA-SLS' as short in the remaining document). The proposed approach first pre-processes the images to reduce the computational complexity. Then, the Convolutional Neural Network (CNN) based ensemble models (off-the-shelf CNN, bagged CNN, and boosted CNN) are implemented and compared. The evaluation results indicate that the performance of bagged CNN is significant. The training and testing accuracy of the bagged CNN is 96.1% and 95.1%, respectively. The main contributions made in this paper are: (1) An automated ensemble learning-based approach is proposed to identify defects in SLS images. To our knowledge, it is the first ensemble learning-based approach for defect detection for SLS powder beds, and (2) The evaluation results indicate that the proposed ensemble learning-based approach accurately identifies defects in SLS images. The training and testing accuracy of bagged CNN is 96.1% and 95.1%, respectively.

The organisation of the rest of the paper is as follows. Section 2 discusses the research background. Section 3 describes the details of the proposed approach. Section 4 describes the evaluation methods for the proposed approach and obtained results. Section 5 concludes the paper.

2 | RELATED WORK

ML algorithms commonly identify defects in various Additive Manufacturing (AM) process stages. Much research has been proposed for defect detection in powder beds. However, machine/deep learning based proposed solutions are discussed in this section. Westphal et al. [14] proposed a CNN-based defect detection in powder beds during selective laser sintering. They generated a dataset of 9426 images and exploited the CNN-based technique on the dataset for defect detection in powder beds. They also implemented VGG-16 models for the classification of images to identify defects. The proposed model's performance (accuracy precision, recall, and F1-score) was 0.958, 0.939, 0.980, and 0.959, respectively.

Xiao et al. [9] proposed a two-stage CNN-based approach for detecting PBDs caused during the powder bed fusion (PBF) process. The proposed technique detects three types of PBDs in the SLS process, that is, warpage, part shifting, and short feed. To this end, 460 images were collected by the digital camera. They used 400 images to train the proposed model, whereas 60 images were used for validation and testing. The proposed approach showed that the accuracy of defect detection was improved significantly. The accuracy of the classifier was 94%, 96%, and 94% for warpage, part shifting, and short feed defects, respectively.

Gobert et al. [19] proposed a Linear Support Vector Machine (SVM) based technique for fault detection during the PBF process. They used a high-resolution Digital Single-Lens Reflex (DSLR) camera to acquire layer-by-layer images of the powder beds. The classifier was trained with the acquired images. The validation results showed that the accuracy of the proposed ML technique was greater than 80%.

Qi et al. [20] proposed a neural network-based approach to identify the defects in AM by performing complex pattern recognition. They analysed several aspects of the laser sintering process, that is, model design, *in–situ* monitoring and quality evaluation. *in–situ* monitoring gives insight into the product's quality based on sensors' inputs. Consequently, it is very important to detect defects during AM process. They used a Spectral Convolutional Neural Network (SCNN) for *in–situ* monitoring. The proposed approach achieved the accuracy of 89% for poor workpiece quality.

Scime et al. [21] introduced a computer vision-trained algorithm to detect and classify the anomalies in the Laser Powder Bed Fusion (LBPF) process. They utilised convolutional Neural Network (CNN) machine learning algorithm. Moreover, CNN is applied on the laser sintering images in layers (Segment-wise). They suggested that M/DL algorithms may provide better accuracy for detecting anomalies in the LBPF process.

Baumgartl et al. [22] analysed the defects occurred during LPBF process. For this purpose, they used off-axis imaging as a data source. They proposed a deep learning-based neural network approach for detecting defects during printing, for example, de-lamination and splatter. The proposed techniques achieved an accuracy of 96.80% for de-lamination and splatter, respectively.

Yadav et al. [23] reviewed the ML techniques for *in–situ* monitoring to detect and monitor defects during the LPBF process. They considered the most prevalent defects during LPBF, for example, lack of fusion, part distortions, and balling. It was concluded in the review article that the *in–situ* monitoring is still in the early stages. The defect detection process should be investigated further for SLS and LPBF processes.

Zhang et al. [24] proposed a neural learning-based approach to detect internal material flaws in metallic Additively Manufactured (AM) materials. They analysed the pulsed thermography (PT) images generated by a high-intensity flash lamp and a high-sensitivity infrared camera to capture temperature variations. Furthermore, they utilised Neural Learning based Blind Source Separation (NLBSS) algorithm to detect experimental thermal imaging data defects. This approach showed promising results for detecting small material defects with signal contrast levels approaching the sensitivity limit of the IR camera. Moreover, merging artificial intelligence (AI) with photo-thermic for non-destructive evaluation (NDE) system detect internal calibrated defects of various sizes and depths in AM nuclear-grade metallic alloys.

Chen et al. [25] proposed a two-stage Convolutional Neural Network (CNN) based approach for defect detection in metal laser melting manufacturing (MAM). In this detection method, images are recorded by powder bed fusion equipment. The proposed approach focuses on three powder-spreading defects, that is, powder-unevenness, powder-uncovered, and re-coater scratches. The proposed method, the Mask-R-CNN network, achieved an accuracy of 0.9272 with a computational time of approximately 0.2197 s per image.

Okaro et al. [26] proposed a semi-supervised machine learning approach for automatically detecting defects in AM images. The proposed semi-supervised machine learning approach utilised Gaussian Mixture Model (GMM). The proposed approach focuses on Laser Powder-Bed Fusion (L-PBF) builds and extracts key features from large sets of photodiode data obtained during the building of 49 tensile test bars. The proposed approach achieved a success rate of 77% for defected AM images. However, in the semi-supervised machine learning approach, the number of expensive certifications are considerably decreased.

In conclusion, although much research has been conducted to detect defects in different domains, the defect detection of the laser sintering process requires automation. Researchers should address defect detection for laser sintering. From this perspective, this research proposes an ensemble learning-based technique with Bagged CNN and boosted CNN approach to detect defects in SLS powder beds.

3 | METHODOLOGY

3.1 | Overview

The outline of ELA-SLS is depicted in Figure 1. The key steps of the approach for defect prediction are as follows:

1. We exploit dataset *SLS Powder bed defects*[1] created by Westphal and Seitz [14].
2. Second, the collected images are pre-processed to reduce computational complexity.
3. Off-the-shelf CNN, bagged CNN, and boosted CNN models are implemented and compared. Notably, Off-the-shelf CNN refers to pre-trained CNN that are readily available and can be used for various tasks without the need for extensive training from scratch.
4. The deep learning ensemble models are trained and tested for defect prediction.

[1] https://data.mendeley.com/datasets/2yzjmp52fw/1, accessed on 15 March 2023.

3.2 | Problem definition

A powder bed p from a set of powder beds P can be presented as follows:

$$p = <i, s> \tag{1}$$

where, i and s represent an image of p and the status of p, respectively.

The main objective of this paper is to design an ensemble learning classification algorithm that can predict the defect in powder beds during SLS process. The defect prediction of a new powder bed p into a defined class c can be represented as a function f as follows:

$$c = f(p) \quad c \in \{perfect, defect\}, \quad p \in P \tag{2}$$

where, c, f, p, and P represent the class: perfect or defect, the classification function of powder bed defect prediction, a powder bed which is an input of the function, and a set of powder beds, respectively.

3.3 | Pre-processing

The images obtained from the dataset are pre-processed before applying ensemble learning techniques. Pre-processing allows us to eliminate the irrelevant and impotent features from the images of powder beds [15]. Pre-proceeding removes the irrelevant black border area by resizing the images, and extracts the optimised centred square images. Moreover, resizing the images result in higher efficiency, processing time and noise reduction. The images before and after pre-processing are presented in Figure 2.

The pre-processing of the powder bed images starts with the images are converted into greyscale to reduce the complexity of computations. Next, the images are resized from 640 × 480 px. to 300 × 300 px. Resizing is done to reduce unnecessary information. After that, the images are normalised by the re-scaling factor of 1/255. Finally, shear rate, height shift, and width shift are adjusted to 0.15, 0.20, and 0.20, respectively.

After the pre-processing of powder bed images, Equation (1) can be represented as follows:

$$p' = <i', s> \tag{3}$$

where, p' and i' present pre-processed powder bed and pre-processed image, respectively.

3.4 | Off-the-shelf Convolutional Neural Network (CNN)

CNN is commonly used to solve complex computer vision-based problems [27]. The CNN approach is also proven very effective in classifying during additive manufacturing [5]. It is a

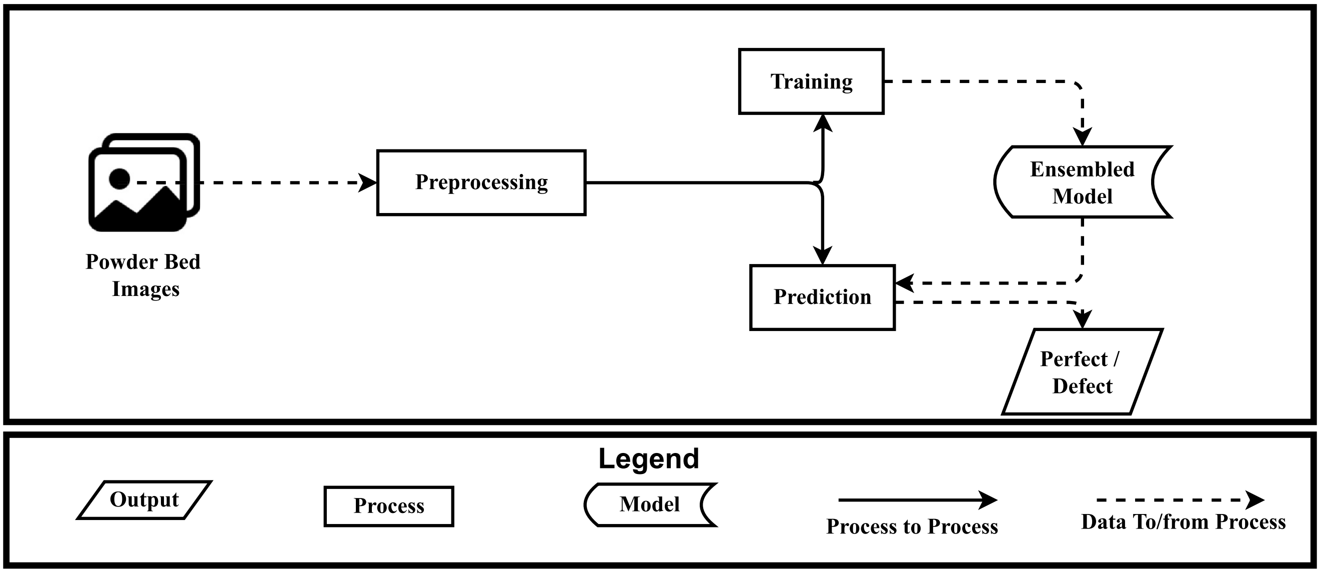


FIGURE 1 Overview of ELA-SLS.

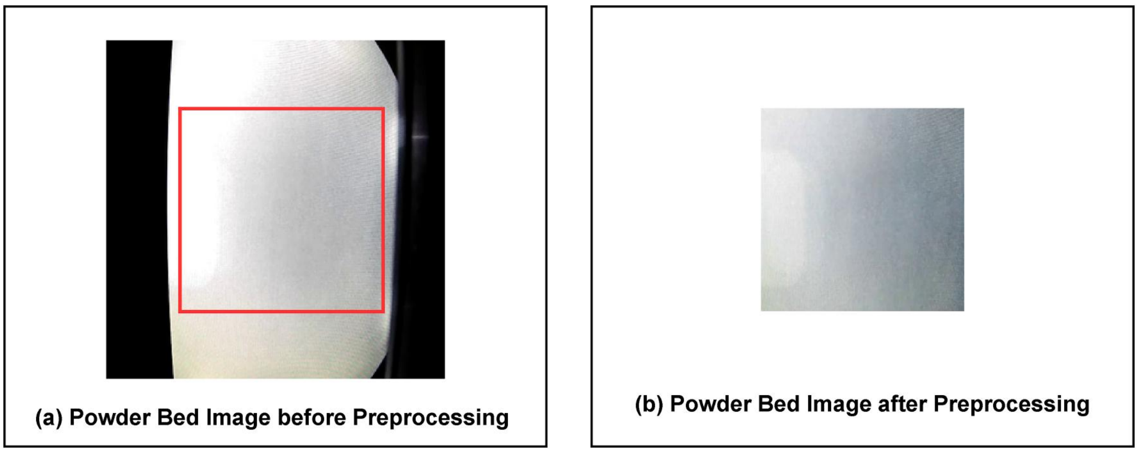


FIGURE 2 Impact of image preprocessing.

multi-layer technique in which the first layer is an input layer, the last layer is an output layer, and at least one convolution layer is used between them. In the convolution layer, multiple filters are modelled to exploit patterns in the powder bed images. Figure 3 shows the multiple-layered model of off-the-shelf CNN.

Three convolution layers are proposed in off-the-shelf CNN. Convolution layer number one, two, and three are defined by Equations (4), (5), and (6), respectively.

$$J_n = f(I_n; \sigma_1, \sigma_2, \ldots, \sigma_k) \tag{4}$$

$$K_n = f(J_n; \omega_1, \omega_2, \ldots, \omega_k) \tag{5}$$

$$L_n = f(K_n; \phi_1, \phi_2, \ldots, \phi_k) \tag{6}$$

where, σ, ω, and ϕ are the filters at layer J_n, K_n, and L, respectively.

Algorithm 1 Bagged CNN.

procedure BAGGED CNN
  Input: X, y, N^m
  Initialise: $p \leftarrow 1$
  while $p \leq N^m$ **do**
    $(X_c, y_c) \leftarrow \int rep(X, y)$ // generate subset (X_p, y_p) of (X, y) for random sampling with a replacement function $\int rep$
    $X_p \xrightarrow{\int_p^m(\sigma, W_p^m, b_p^m)} y_p$ // Training of the 'pth' model in an ensemble using the (X_p, y_p)
    $p \leftarrow p + 1$
  end while
  Output: $\int_1^m(\sigma, W_1^m, b_1^m), \ldots, \int_N^m(\sigma, W_{N^m}^m, b_{N^m}^m)$
end procedure

where, X, y, N, c, X_c, y_c, $\int rep$, σ, W, b, and $\int_1^m(\sigma, W_1^m, b_1^m), \ldots, \int_N^m(\sigma, W_{N_m}^m, b_{N_m}^m)$ are input features, an instance of the occurrence of a SLS powder bed defects, number of the models in bagging, current model, features subset X for c model, y_c is the instance of defects for c model, replacement function, non-linear activation function, weights, bias, and set of models in bagging.

3.5 | Ensemble models

Ensemble learning methods are used in deep learning tasks that combine multiple base-learners [18]. Ensemble learning methods are used in many advanced deep learning problems. Moreover, ensemble learning methods improve the detective performance of the classifier. Three basic steps are involved in ensemble learning models. First, the Ensemble learner extracts the set of features. Second, multiple deep learning algorithms generate detection results based on the extracted features. Third, the generated information extracted by various deep learning algorithms is fused to achieve better detection results [28]. Boosting and bagging are well-known ensemble learning methods [29]. Boosted CNN and Bagged CNN ensemble learning models are proposed in this paper. Both models are constructed to analyse the defects in powder beds during SLS process, where bagging involves training multiple CNN instances with slightly different datasets, adopting model robustness, generalisation, and defence against overfitting. Boosting involves iteratively training a sequence of feeble classifiers to construct a potent ensemble classifier. This ensemble methodology capitalises on diverse model strengths, potentially yielding improved performance and deeper comprehension of intrinsic features and patterns for good and defective image classification. The proposed approach explores the potential advantages and effectiveness of bagging and boosting techniques in laser sintering image classification.

The proposed approach incorporates the Gradient-weighted Class Activation Mapping (Grad-CAM) technique, which is utilised to highlight significant regions and features within images visually. These identified features play a crucial role in classifying good and defective images. Grad-CAM generates informative heat maps that pinpoint the specific areas in an image that have the greatest influence on the neural network's decision-making process.

To generate a class activation map, Grad-CAM combines the gradient information from the final convolutional layer of a convolutional neural network (CNN) with global average pooling. This map effectively emphasises the regions in the input image that contribute most significantly to the predicted class.

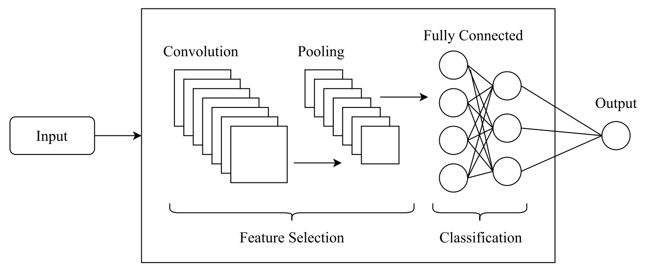


FIGURE 3 Off-the-shelf Convolutional Neural Network (CNN) architecture.

3.5.1 | Bagged CNN

In the bagged CNN algorithm, multiple models are trained on a subset of extracted features. Multiple off-the-shelf CNN algorithms are applied to the subset, generating a single output from each model. The individual outputs of off-the-shelf CNN results aggregate in the one output of the bagged CNN. Figure 4b demonstrates the bagged CNN architecture. The mathematical expression of the output is given in Equation (7). Moreover, the algorithm of bagged CNN is given in Algorithm 1.

$$\int_1^m(\delta, W_1^m, b_1^m), \int_2^m(\delta, W_2^m, b_2^m), \ldots, \int_N^m(\delta, W_{N_m}^m, b_{N_m}^m) \tag{7}$$

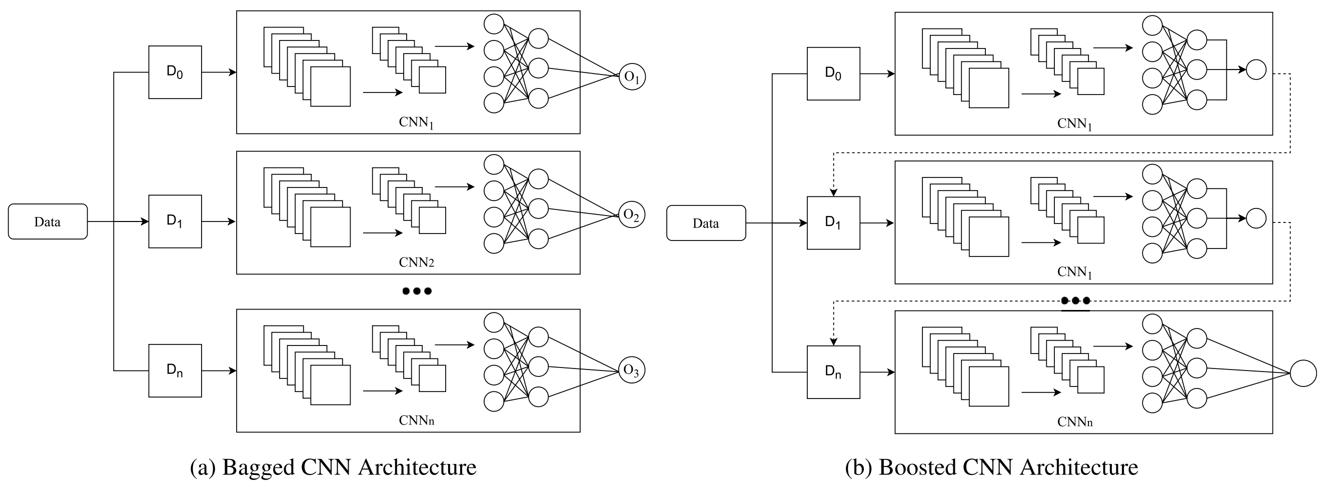


FIGURE 4 Architecture of off-the-shelf, bagged, and boosted Convolutional Neural Network (CNN).

3.5.2 | Boosted CNN

In boosted CNN algorithm, multiple models are also trained on a subset of extracted features. However, the output of each CNN model is feedback as input to the preceding CNN model. CNN learns hierarchically abstracted features from images. However, CNN only learns features through a feed-forward structure, and no feedback information from top to bottom layers is in its structure to enable the networks to refine themselves. Therefore, a feedback layer is added in boosted CNN to boost the performance based on the previous prediction recurrently. The same process is repeated until nth CNN achieves a single output. Figure 4a demonstrates the boosted CNN architecture. Moreover, the algorithm of boosted CNN is given in Algorithm 2. The configuration of bagged CNN and Boosted CNN are presented in Table 1.

Algorithm 2 Algorithm of boosted CNN.

procedure BOOSTED CNN
    Input: X, y, N^b, α^t
    Initialise: $p \leftarrow 2$
    $X \xrightarrow{\int_1^b(\sigma, W_1^b, b_1^b)} y$ // Train Initial model (X, y)
    while $p \le N^b$ **do**
    $t_{temp} \leftarrow y - \alpha^b \sum_{q=1}^{p=1} \int_q^b (.)$
    $X \xrightarrow{\int_p^b(\sigma, W_p^b, b_p^b)} y_{temp}$ // Train Initial model (X, y)
    $p = p + 1$
    end while
    Output: $\int_1^b(\sigma, W_1^b, b_1^b), \ldots, \int_N^b(\sigma, W_{N\,bm}^{\,b}, b_{N\,bm}^{\,b})$
end procedure

where, X, y, N, c, σ, W, b, $\int_1^b(\sigma, W_1^b, b_1^b)$, and $\int_1^b(\sigma, W_1^b, b_1^b), \ldots, \int_N^b(\sigma, W_{N\,bm}^{\,b}, b_{N\,bm}^{\,b})$ are input features, an instance of the occurrence of a SLS powder bed defects, number of the models in bagging, current model, non-linear activation function, weights, bias, cth model, and set of models in boosting.

4 | EVALUATIONS

This section introduces the research questions, dataset, and selected experiment metrics, provides the experiment results by investigating the research questions, and explains the threats to validity of ELA-SLS.

4.1 | Research questions (RQs)

- RQ1: Does ELA-SLS surpasses the baseline approaches? if yes, to what extent?
- RQ2: Does pre-processing of dataset images affect the working of ELA-SLS?

We compare off-the-shelf CNN, bagged CNN (the proposed approach), and boosted CNN to check the performance of ELA-SLS as an investigation of RQ1.

We compare the performance results of bagged CNN by enabling and disabling the pre-processing step to check the impact of pre-processing on ELA-SLS as an investigation of RQ2.

4.2 | Metrics

We compute the accuracy and loss during the training and testing of ELA-SLS for its performance evaluation.

Accuracy is a measurement that gives insight into model performance. The accuracy is measured by taking the ratio of correct defects detection to the total defects detection. The mathematical expression of accuracy is given by Equation (8).

$$Accuracy = \frac{Correct\ Defect\ Detections}{Total\ Detections} \tag{8}$$

The computation of the performance loss is critical in evaluating the performance of the ensemble learning algorithms. Loss is measured by taking the difference between the detected and actual values. The mathematical expression of loss is expressed in Equation (9).

$$Loss = abs(Model\ Predicted\ Value - Actual\ Value) \tag{9}$$

This binary classification measures the loss in cross-entropy form (log loss). The mathematical expression of log loss is expressed in Equation (10).

$$LogLoss = \frac{1}{N}\sum_{i=0}^{N} -\left(y_i \times \log(p_i) + (1 - y_i) \times \log(1 - p_i)\right) \tag{10}$$

TABLE 1 Configurations of bagged and boosted Convolutional Neural Networks (CNNs).

Parameter	Value
No hidden layers	2
Activation function (input layer)	Relu
Activation function (output layer)	Sigmoid
Optimiser	Adam
No. of epochs	300
No. of nodes (input layer)	46
No. of nodes (hidden layer 1)	46
No. of nodes (hidden layer 2)	30
No. of nodes (output layer)	1

where, p_i is the probability of occurrence of defects in powder beds, and $(1 - p_i)$ is the probability of occurrence of non-defects in powder beds.

4.3 | Dataset

We exploit dataset *SLS Powder bed defects*[1] created by Westphal and Seitz [14], to measure the performance of the proposed defect prediction model. The samples images of good powder bed and defected powder bed are shown in Figure 5a, b, respectively. The images presented in Figure 5b illustrate the irregularities and inconsistencies caused during the laser sintering process. The dataset contains 8514 powder bed images of 640 × 480 px resolution of both classes: defected and uniform powder bed images. Note that the performance of off-the-shelf CNN, bagged CNN, and boosted CNN is evaluated based on selected metrics. The 80% of the data is used for training, and 20% of the data is used for testing for the evaluation of ELA-SLS. Although the common approach is using a 0.8/0.1/0.1 split for training, testing, and validation, it can be prone to data leakage and data overlapping is possible. Therefore, the dataset is shuffled before the training and testing categorisation (80%:20%) of images to avoid biasness.

4.4 | Evaluation results

4.4.1 | RQ1: Performance of ELA-SLS

To answer the RQ, the accuracy is evaluated for three hundred (300) epochs for the selected classifier. The evaluation results of off-the-shelf CNN, bagged CNN, and boosted CNN are demonstrated in Figure 6.

The following observations are made from Figure 6a–d.

- The training and testing accuracy of bagged CNN is 96.1% and 95.1%, respectively. The accuracy of bagged CNN for 300 epochs is presented in Figure 6b. The bagged CNN model is designed and trained to establish a balance among different variables, the count of bags (distinct subsets of training data), and the allocation of resources within the network's architectural framework. It is evident from Figure 6b that the bagged CNN is in a balanced shape. Although the performance of the existing approach [14] is close to the proposed approach, the proposed approach introduces an ensemble learning CNN method of image classification rather than using the Off-the-shelf CNN approach exploited by Westphal and Seitz [14].
- The training and testing accuracy of boosted CNN is 94.8% and 94%, respectively. The accuracy of bagged CNN for 300 epochs is presented in Figure 6c. It is evident from Figure 6c that the boosted CNN is in a balanced shape. However, the accuracy of bagged CNN is better than the boosted CNN.
- The training and testing accuracy of off-the-shelf CNN is 86.3% and 86.2%, respectively. The accuracy of off-the-shelf CNN for 300 epochs is presented in Figure 6a. It is evident from Figure 6a that the off-the-shelf CNN is also in a balanced shape. However, the accuracy of off-the-shelf CNN is worse than the bagged and boosted CNN.
- The training/testing accuracy performance of bagged CNN, boosted CNN, and Off-the-Shelf CNN is compared to analyse these results. The comparison of the accuracy of all the models is presented in Figure 6d. The accuracy of bagged and boosted CNN is better than off-the-shelf CNN. Moreover, the accuracy of bagged CNN is better boosted CNN. It is concluded that the accuracy of bagged CNN is better for detecting defects in powder beds than boosted CNN and off-the-shelf CNN.

Furthermore, we compute the loss of bagged CNN, boosted CNN, and off-the-shelf CNN. The evaluation results of these approaches are demonstrated in Figure 7 which are evaluated for three hundred epochs.

The following observations are made from Figure 7a–d.

- The training and testing log losses of bagged CNN are 0.0273 and 0.031, respectively. The loss of bagged CNN for 300 epochs is presented in Figure 7b.
- The training and testing log losses of boosted CNN are 0.031 and 0.03247, respectively. The loss of bagged CNN for 300 epochs is presented in Figure 7c. Compared to bagged CNN, the values of log losses are higher in boosted CNN.
- The training and testing log losses of off-the-shelf CNN are 0.042 and 0.043, respectively. The loss of bagged CNN for

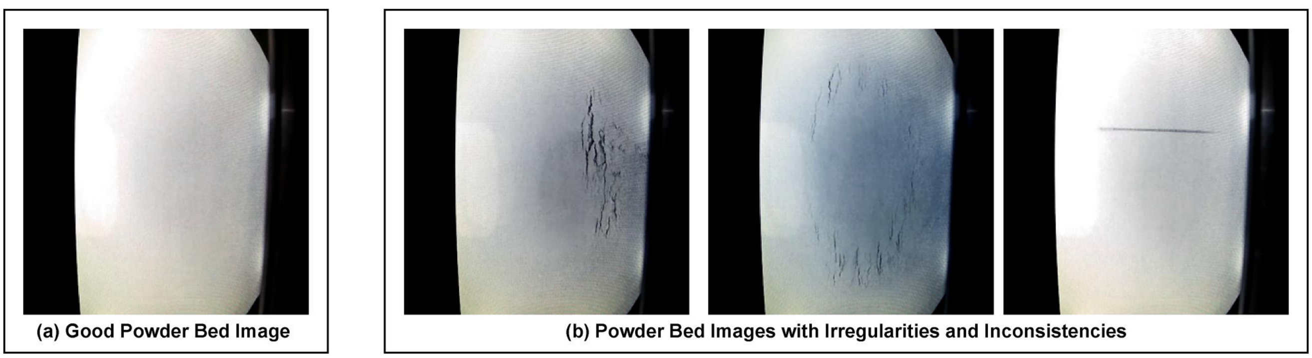
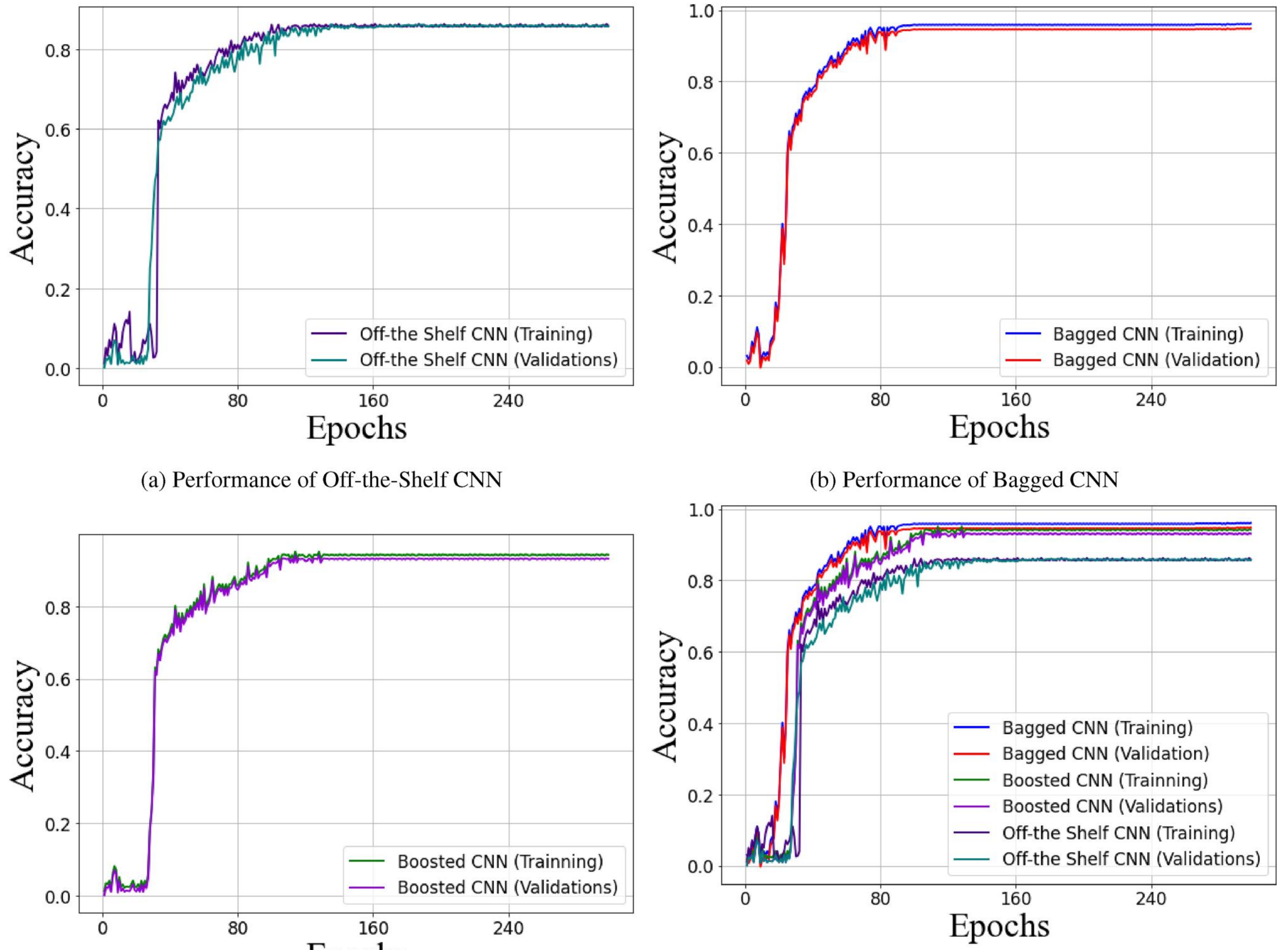


FIGURE 5 Samples of defected powder beds from the exploited dataset.



(a) Performance of Off-the-Shelf CNN

(b) Performance of Bagged CNN

(c) Performance of Boosted CNN

(d) Performance Comparison of Bagged CNN, Boosted CNN, and Off-the-Shelf CNN

FIGURE 6 Performance (accuracy) of off-the-shelf, bagged, and boosted Convolutional Neural Network (CNN).

300 epochs is presented in Figure 7a. The values of log losses of off-the-shelf CNN are higher than boosted CNN.

- To compare the log losses of bagged CNN, boosted CNN, and off-the-shelf CNN, the losses are evaluated and compared over 300 epochs, which is presented in Figure 7d. It is evident from these log loss results that off-the-shelf CNN is the least efficient. Moreover, bagged CNN has the lowest value of losses, and it is the most efficient technique to detect the defects in powder beds.

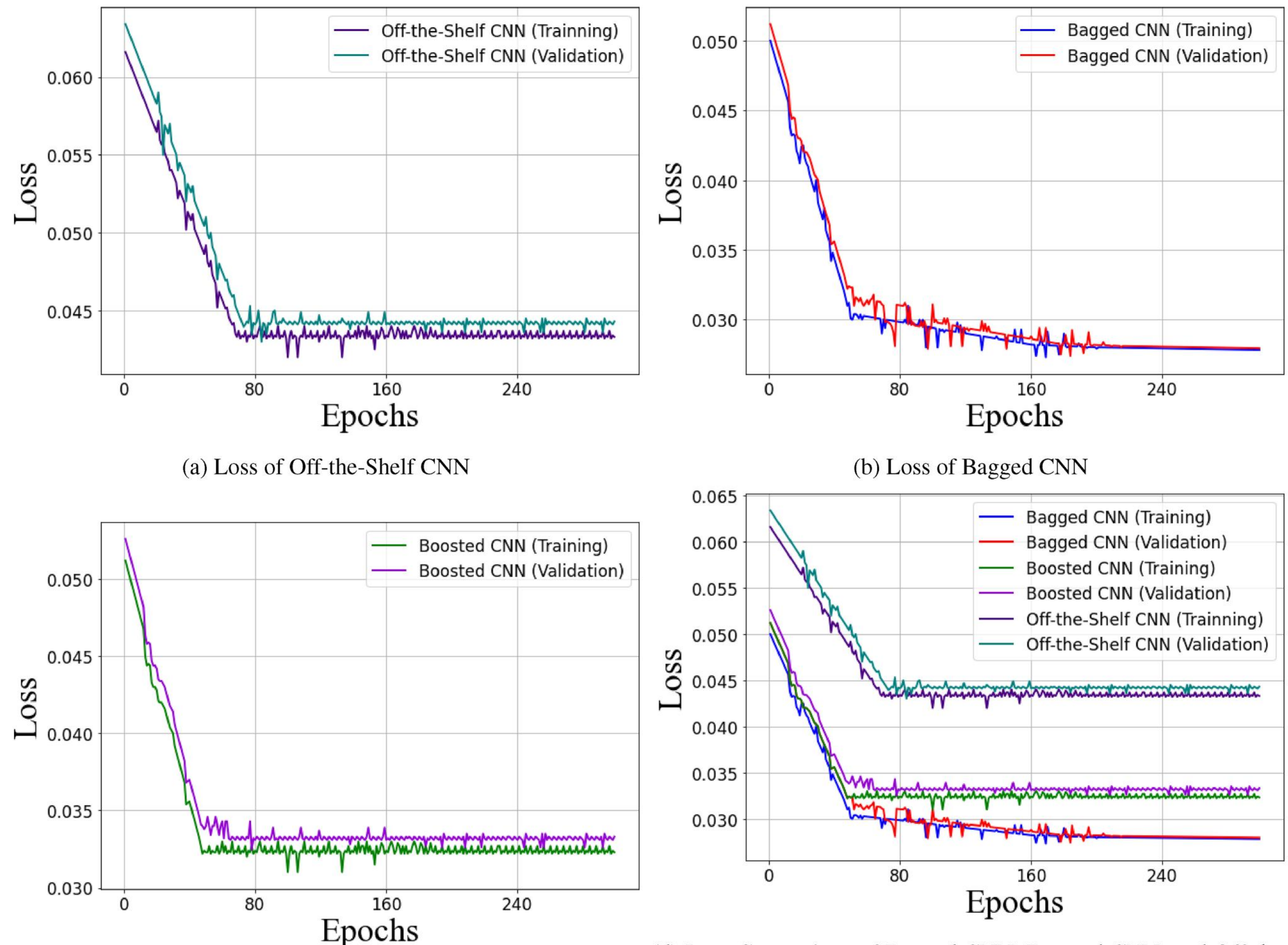
The preceding analysis indicates that the performance of bagged CNN is significant is contrast to off-the-shelf and boosted CNN in defect detection for SLS powder beds.

4.4.2 | RQ2: Influence of preprocessing on ELA-SLS

The evaluation results of ELA-SLS are presented in Table 2. The evaluation results of ELA-SLS for different settings of pre-processing (enable/disable) based on their accuracy and loss are (95.01% and 0.31) and (90.56% and 0.38), respectively.

From Table 2, it is observed that disabling pre-processing brings out the significant difference in accuracy from 95.01% to 90.56% and loss from 0.31 to 0.38. It is concluded that pre-processing of images is critical for detecting defects, and disabling it would significantly reduce the performance of ELA-SLS.

In conclusion, the proposed approach is significant for the classification of powder bed images and important for the laser science community. For example, powder bed images obtained during the additive manufacturing process contain valuable information about the quality and integrity of the printed parts. The proposed approach can effectively detect and classify various defects, that is, cracks, porosity, or incomplete fusion, and could be helpful in real-time monitoring of the powder bed during the additive manufacturing process. By continuously analysing the images, these models can detect anomalies or deviations from expected patterns, allowing immediate intervention if a defect or issue arises.



(a) Loss of Off-the-Shelf CNN

(b) Loss of Bagged CNN

(c) Loss of Boosted CNN

(d) Loss Comparison of Bagged CNN, Boosted CNN, and Off-the-Shelf CNN

FIGURE 7 Losses of off-the-shelf, bagged, and boosted Convolutional Neural Network (CNN).

TABLE 2 Influence of preprocessing on bagged Convolutional Neural Network (CNN).

Preprocessing	Accuracy	Loss
Enable	95.01%	0.31%
Disable	90.56%	0.38%

4.5 | Threats to validity

The probability of incorrect classification of powder bed images is the first threat to construct validity. This research assumes that the assigned labels by Westphal and Seitz [14] are correct. However, incorrect labelling of data may cause the productivity of ELA-SLS.

The choice of assessment metrics of ELD-SLS is another threat to construct validity. The chosen metrics for detecting news are the most accepted in the literature for the classification task.

The coding of off-the-shelf CNN, bagged CNN, and boosted CNN is a threat to internal validity. The coding and the produced results of ELA-SLS for all variants are verified to mitigate the threat. However, unknown errors may cause the productivity of ELA-SLS.

5 | CONCLUSION

The paper proposes an ensemble learning-based approach to predicting defects in powder beds during SLS process. Off-the-shelf CNN, boosted CNN, and bagged CNN techniques are implemented and evaluated to achieve the objective. The proposed models are evaluated with an open-source dataset collected from Kaggle. It was evident from the comparative results that both ensemble learning models, that is, boosted CNN and bagged CNN performed better than off-the-shelf CNN. Moreover, bagged CNN is the most accurate for detecting defects in powder beds. The results also indicate that pre-processing of the images, mainly cropping to the region of interest, improves the performance of the proposed approach.

Our aim for the future is to enhance the comprehensibility of detection algorithms. Currently, these algorithms frequently employ complex deep learning models that lack transparency, resulting in a challenge to discern the reasoning behind their decisions. To address this issue, future research may concentrate on creating more transparent models or instruments that facilitate users in comprehending the decision-making process of these algorithms.

AUTHOR CONTRIBUTIONS

Junyi Xin: Conceptualization; methodology; software; visualization; writing—original draft. **Muhammad Faheem**: Data curation; investigation; methodology; validation; writing—review & editing. **Qasim Umer**: Investigation; formal analysis; resources; supervision; writing—review & editing. **Muhammad Tausif**: Data curation; formal analysis; investigation; validation. **M. Waqar Ashraf**: Data curation; investigation; validation.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available in Mendeley Data at DOI: 10.17632/2yzjmp52fw.1. These data were derived from the following resources available in the public domain: https://data.mendeley.com/datasets/2yzjmp52fw/1.

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