Taguchi based Design of Sequential Convolution Neural Network for Classification of Defective Fasteners*

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Abstract. Fasteners play a critical role in securing various parts of machinery. Deformations such as dents, cracks, and scratches on the surface of fasteners are caused by material properties and incorrect handling of equipment during production processes. As a result, quality control is required to ensure safe and reliable operations. The existing defect inspection method relies on manual examination, which consumes a significant amount of time, money, and other resources; also, accuracy cannot be guaranteed due to human error. Automatic defect detection systems have proven impactful over the manual inspection technique for defect analysis. However, computational techniques such as convolutional neural networks (CNN) and deep learning-based approaches are evolutionary methods. By carefully selecting the design parameter values, the full potential of CNN can be realised. Using Taguchi based design of experiments and analysis, an attempt has been made to develop a robust automatic system in this study. The dataset used to train the system has been created manually for M14 size nuts having two labeled classes: Defective and Non-defective. There are a total of 264 images in the dataset. The proposed sequential CNN comes up with a 96.3% validation accuracy, 0.277 validation loss at 0.001 learning rate.

Keywords: Fasteners · Sequential Convolution Neural Network · Defects · Taguchi analysis.

1 Introduction

Bolts and nuts are common fasteners in the mechanical and automotive industries. Cold forming, hot forming, thread production, machining, hardening and tempering are the procedures that fasteners go through throughout production [3]. Changes in the material’s intrinsic characteristics, effect of vibrations, tool damage, and improper process management can result in flaws in the end products as fasteners because of the processes they go through [5]. Fastener raw

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materials might often develop cracks. Wrinkles are a form of imperfection on
fasteners caused by material displacement during the forging process of nuts
in particular. Deformation, dents, wrinkles, scratches, fractures, rough surface,
missing and misaligned threads on the fastener surface are all faults generated
by processing [20]. Small and medium-sized industries are the largest manufac-
turers of these fasteners but the process of inspection is done manually, which
requires a lot of people, money, and time. Even with all of that work, the po-
tential for errors still exists, and defective products may reach clients. As a
result of the vibration, these defective fasteners may lose up, or even break in
long-term [21]. The development of automation technologies to detect bad steel
fasteners could help in overcoming this challenge. The machine learning defect
detection system reduced human error and effort, it makes the procedure more
accurate by detecting defects that might otherwise go unnoticed by humans [4].
The process involved calculating a collection of hand-crafted textural characteristics, which were afterward trained on a classifier [14]. Although the automated
detection process based on image processing and machine learning techniques
offered great benefits it has some major drawbacks. One of the most significant
is that the appearance of abnormalities changes in terms of form, size, colour,
geometry, and other factors even within the same inspection work [15]. Due to
these reasons computer vision applications and deep learning based convolution
neural network (CNN) can be used for better efficiency and precise detection
rate.

2 Related Work

Computer vision-based applications for object detection and classification using transfer learning and traditional CNNs are emerging and have become very
popular in software, mechanical and electrical industrial sectors. The amount
of speed, efficiency, and robustness provided by these applications has made
day-to-day work simple [11]. There are a lot of examples where the use of such
deep learning models for the detection and classification of industrial fasteners
has proved to be successful in achieving the goal of high accuracy in less time.
Some of the examples where computer vision has exceptional contributions are
taken into consideration before proposing the model. Several algorithms have
been used for metal crack detection and texture feature extraction. Different
edge detection operators have been used to obtain thin edge features on defec-
tive samples [19]. Similarly several machine learning based techniques, have been
explored for classification of surface defects on rolled steel [3]. Sharifzadeh et al.
applied Gaussian functions and histogram approaches to detect various flaws on
steel components, with a detection rate of 88.4% for holes, 78% for scratches,
90.4% for coil breaks, and 90.3% for rust problems [16]. Ashour et al. applied
support vector machine to inspect the visual texture feature from the sample
data, also different kernel functions has been investigated for best performance
classifier [1]. Park et al. proposed machine learning based imaging based system
for defect detection for dirt, scratches, and wears on surface. CNN has been ap-
plied to check the existence of defect in the target region on an input sample image. The proposed method has been proven to be advantageous in terms of time, cost and performance as compared to manual inspection techniques [13]. Bhandari and Deshpande proposed a modified scheme based on heuristics algorithm used by human inspectors for identifying surface imperfections to compute the features, then used SVM to classify surface images into two classes: defective and defect-free. The system was tested on a surface texture database and achieved a classification accuracy of 94.19% [2]. Zhao et al. investigated computer vision to detect pin missing problems in transmission lines that employed bolts to link different components. Defects in these bolts can cause major problems, such as grid breakdown. To solve this problem, a CNN model was proposed, which included three key improvements for extracting small-scale bolt features and achieved a 71.4% accuracy [22]. A version of CNN architecture was used by Liu et al. to detect catenary support components (CSCs). It involved the integration of a detection network for CSCs utilising large scale optimized and improved Faster R-CNN with a cascade network for the detection of CSCs with small scales. The model has a good accuracy of 92.8% [9]. Taheritanjani et al. created a system that automatically recorded, preprocessed data and compared it to a variety of supervised and unsupervised machine learning models for detecting damage in 12 different fasteners. The method also helped in determining the type of fastener used. The supervised model achieved 99%, whereas the unsupervised model achieves 84% [18]. Giben et al. proposed a visual inspection method for semantic segmentation and classification of material using deep convolution neural network (DCNN). In this approach they identified ten kinds of materials in total using this method, and the proposed model had a classification accuracy of 93.35%. The detection rate for chipped and crumbling ties was 92.11% and 86.06%, respectively [7]. To extract rich feature information, Kou et al. used specifically built dense convolution blocks in their defect detection model, which significantly increases feature reuse, feature propagation, and the network’s characterization ability. The suggested model generated 71.3% mean Average Precision (mAP) on the GC10-DET dataset, which is publicly available, and 72.2% mAP on the NEUDET dataset [8]. Song et al. presented a CNN based technique in which they consider damage screw, surface dirt and stripped screw as defective classes, images has been taken up with industrial camera. Proposed model achieve 98% accuracy with 1.2s of average time taken to process per image [17]. Gai et al. proposed a CNN technique for detecting defects on steel surfaces in industrial parts. An industrial camera was used to collect and pre-process the data, and then the VGG architecture was used to improve network features, classification, and defect recognition capability. The proposed model was then compared to other traditional strategies and found to be more effective [6]. Computer vision-based applications such as object identification and classification using transfer learning or traditional CNNs have grown increasingly popular in all industries. The speed, efficiency, and robustness provided by these approaches have simplified day-to-day tasks. Researchers have employed the transfer learning approach in defect categorization but these mod-
els were trained on datasets for object detection and have no resemblance to the
defect detection domain. Due to the fundamental difference between the object
detection and defect detection domains, CNN models must be built from the
scratch and trained on good quality dataset. Furthermore, the lack of standard
datasets leads to erroneous and inconclusive findings, and there is currently no
model that can be right away used for transfer learning. This work proposes a
dataset of defects on the nuts and a design of sequential CNN model to han-
dle these two key difficulties. This study also demonstrates the efficacy of the
Taguchi strategy, which is a simple yet effective method for handling parameter
optimization problems. The proposed method aids in determining the sequential
CNN parameter value for defect classification in fasteners, according to the
results.

Fig. 1. Proposed Workflow for Taguchi based Design of Sequential Convolution Neural
Network (CNN).
3 Proposed Framework for Taguchi based Design of Sequential Convolution Neural Network (CNN)

Fig. 1 shows the proposed framework for designing an optimized sequential CNN model. The details of each step are as presented below:

3.1 Dataset Preparation

In order to prepare a practical dataset, samples of M14 size nuts with six side faces have been collected from the fastener industries. The images of size 1844*4000 pixels were captured by mobile phone camera in variable light conditions by varying the level of illumination. Image of each face of nut is captured. The real world captured dataset had the problem of class imbalance, as the number of non-defective sides of nut were more than the defective samples. To enhance the number of defective images in the dataset, augmentation in terms of scaling and brightness variation was applied. This resulted in 132 images each in ‘Defective’ and ‘Non-Defective’ class. 80% of images were used for the training set and 20% for the test set. Fig. 2 shows the sample images from dataset. The most common types of defects are crack, dent, patches, scratches and wrinkles [6]. Here, all the defects are considered as a single class as ‘Defective’.

![Sample Images M14 Size Nuts in Dataset](image)

**Fig. 2.** Sample Images M14 Size Nuts in Dataset.

3.2 Sequential CNN Design Parameters

The architecture of a basic sequential CNN is as depicted in Fig. 3. These architectures can be created from scratch. To create a CNN model for a given application, early layers learn low-level characteristics, while the end-layer conducts classification based on the feature map.
Number of CNN Layers  The CNN structures are motivated by the fact that increase in number of layers help in better approximation of target function and enhances the capability to learn from more detailed feature set. This makes, the number of layer as one of the essential dimension in regulating learning ability of the sequential architecture.

Input Image Size  Image size is chosen such that the fine defects such as cracks and scratches are clearly visible but larger input image size leads to more number of input is visible. However, having larger size input image leads to increase in complexity of CNN. Therefore, [100x100] and [200x200] are selected for the study. If a coloured image of 100 pixels in height and width is supplied, each pixel has one single channel, and the input layer has the form (100, 100, 3).

Optimizer  An optimizer updates the model with respect to the loss function and help in minimizing it by calculating partial derivative of the loss corresponding to weights and updating the weights in the direction opposite of the obtained gradient. This process is repeated until the loss function’s minima is reached. Gradient descent takes into account the learning rate and takes larger steps if the loss is large and a smaller steps if loss is decreasing. The purpose of small learning rate is to come close to minimum value. The objective function is optimised using Stochastic Gradient Descent (SGD). It replaces the gradient with a value computed from a randomly picked data subset, this can be considered a probabilistic estimate to steepest descent. As a result, specific samples are chosen rather than the entire dataset. The global minimum can be readily attained, but when dealing with a large dataset becomes more difficult, hence SGD takes approximation of gradient descent by selecting a subset of samples. It can be particularly helpful in the case of large dataset. Adaptive Moment Estimation (ADAM) scales the learning rate using an exponentially weighted gradient. It is one of the most popular gradient descent optimizer algorithms. It keeps the
record of the average of earlier gradients that are decreasing. It is a very effective optimizer that requires very little memory and has a low training cost.

**Loss Function** Hinge rank loss aims to reduce the spread between the output of the model and the target vector while isolating it from all the other vectors, thus penalizing equally all the errors. Squared hinge loss computes the square of hinge loss, resulting in flat error function’s surface and also making it numerically simple to handle. If a hinge loss improves performance on a binary classification issue, most probably a squared hinge loss will improve performance even more.

**Activation Function** Rectified Linear Unit (ReLU) is a non-linear activation function to calculate activations of convolved feature map. ReLU response maximizes beyond a certain point away from zero and has a V-shape, whereas the response is capped to the maximum value of 6 giving it a Z-shape.

**Filter Size** The purpose of implementing CNN is to extract key features from the input images that can characterize a class. Convolutional operation considers the local subset of pixels, therefore different levels of subsets can be explored in the image by using different filter sizes and variation in filter size capture different details. A small size filters find fine details by exploring the small regions in the image. While, large size filter finds coarse information and the model tries to find features in a large area of the input at each computation. Hence, spatial filters can be explored to improve performance with regard to learning aspect of the network. By carefully adjusting the filters, CNN can perform well both on coarse and fine details. In this research, an attempt is made to experiment with these basic building elements of sequential CNN in order to identify the best combination that will allow the model to perform well. The influence of each parameter adjustment and its combinations can be better understood by carefully designing the experiments.

### 3.3 Taguchi based Grid search for CNN design Parameters

**Taguchi based grid search** approach is relevant to all the real-world design problems which depends on number of control factors or hyperparameters. Taguchi’s orthogonal array has been used in the design of experiments [10]. It is found out to be proficient when paralleled to many other statistical designs [13]. Value of control factors must be determined in order to achieve the optimal results. Taguchi analysis aims to enhance quality as a way to deliver resilient configurations and design. The term "signal" refers to improved performance with little variance, which is referred to as “noise.” The consistency of performance is a metric of robustness, which is achieved by making the design immune to the effects of uncontrollable characteristics. A two-step optimization procedure is used in Taguchi grid search. Selection of hyper parameters and desired modifications is the initial stage. Next, the orthogonal array is chosen to ensure
that these control components participate equally and in a planned manner [12].
The best potential performance is produced in the second stage by identifying
the best arrangement of hyperparameters.

**Selection of Hyperparameters** Variations in object size, and distance from
the camera are sources of variation (noise) in the defect categorization domain.
The aim is to find the optimum hyperparameter combination that delivers high
performance when subjected to fluctuations. Table 1 lists the description, value
of parameters variation while performing trials. Since there is one component
with four levels and five factors with two levels, L16 is the best choice among
the Taguchi mixed level design possibilities for six parameters. A total of 36 trials
will be required if the complete factorial design with all possible combinations is
used. However, utilising Taguchi’s orthogonal array to properly design trials,
the total number of trials that must be examined for testing is reduced to 16 as
indicated in Table 2.

| Factors (6) | Name of parameter | Variations/Levels |
|-------------|-------------------|-------------------|
| A           | No. of CNN Layers | 6, 8, 10, 12      |
| B           | Image Size        | [100x100], [200x200] |
| C           | Optimizer         | adam, sgd         |
| D           | Loss Function     | Hinge, Squared Hinge |
| E           | Activation Function | ReLU, ReLU6       |
| F           | Filter Size       | [2x2], [3x3]      |

**Selection of Response Parameters** In this work, the response parameters
or performance metrics that are used to assess performance are test accuracy,
validation accuracy, test loss and validation loss. The purpose is to maximize
accuracy and minimize loss.

4 Analysis of Results

The model is implemented with Python software, and the DOE analysis is done
with Minitab. The recommended set of parameters has been fine-tuned for the
fastener dataset. The outcome of experiments for the possible set of combinations
are recorded, each training is conducted for 500 epochs and the best result are
recorded. Table 2 is analysed using Taguchi’s analysis in a Minitab tool. The
highlighted text indicates the best results in Table 2.

**Interval Plot** for variation in values in train loss, train accuracy, validation loss
and validation accuracy is shown in Fig. 4. It is used to evaluate and compare
confidence intervals for result means. An interval plot depicts a 95% confidence
Table 2. Experimental Outcome as per Taguchi’s L16 Orthogonal Array.

| Exp. Run | Parameter Variation | Response Values |
|----------|---------------------|-----------------|
| A        | B                  | C               | D    | E     | F     | Train Loss | Train Accuracy | Val. Loss | Val. Accuracy |
| 1. 6     | 100x100            | adam            | Hinge | ReLU  | 2x2   | 0.3885     | 0.9251       | 0.9303     | 0.9145       |
| 2. 6     | 100x100            | adam            | Hinge | ReLU  | 3x3   | 0.6127     | 0.8508       | 0.7954     | 0.8629       |
| 3. 6     | 200x200            | sgd             | Sqd.  | Hinge | ReLU  | 2x2   | 0.3539     | 0.7552       | 0.6096     | 0.6721       |
| 4. 6     | 200x200            | sgd             | Sqd.  | Hinge | ReLU  | 3x3   | 0.5114     | 0.9091       | 0.8036     | 0.8966       |
| 5. 8     | 100x100            | adam            | Sqd.  | Hinge | ReLU  | 2x2   | 0.1441     | 0.8449       | 1.6285     | 0.8497       |
| 6. 8     | 100x100            | adam            | Sqd.  | Hinge | ReLU  | 3x3   | 0.5757     | 0.8545       | 0.7945     | 0.8397       |
| 7. 8     | 200x200            | sgd             | Hinge | ReLU  | 2x2   | 0.275      | 0.1983      | 0.579      | 0.1883       |
| 8. 8     | 200x200            | sgd             | Hinge | ReLU  | 3x3   | 0.2206     | 0.9027      | 0.4843     | 0.9151       |
| 9. 10    | 100x100            | sgd             | Hinge | ReLU  | 2x2   | 0.3332     | 0.9455      | 0.6477     | 0.9433       |
| 10. 10   | 100x100            | sgd             | Hinge | ReLU  | 3x3   | 0.2258     | 0.9273      | 0.5374     | 0.9201       |
| 11. 10   | 200x200            | adam            | Sqd.  | Hinge | ReLU  | 2x2   | 0.0762     | 0.8949      | 0.3033     | 0.9021       |
| 12. 10   | 200x200            | adam            | Sqd.  | Hinge | ReLU  | 3x3   | 0.3889     | 0.9536      | 0.7223     | 0.9433       |
| 13. 12   | 100x100            | sgd             | Sqd.  | Hinge | ReLU  | 2x2   | 0.3889     | 0.9455      | 0.6691     | 0.9433       |
| 14. 12   | 100x100            | sgd             | Sqd.  | Hinge | ReLU  | 3x3   | 0.3626     | 0.9455      | 0.4624     | 0.9433       |
| 15. 12   | 200x200            | adam            | Hinge | ReLU  | 2x2   | 0.1161     | 0.8545      | 0.5709     | 0.8528       |
| 16. 12   | 200x200            | adam            | Hinge | ReLU  | 3x3   | 0.1911     | 0.9159      | 0.3713     | 0.9216       |

The plot indicates that the mean value of train and validation accuracy is almost equal with similar variability, while the loss values show clear displacement in terms of mean average value. The validation loss has a lot of variability and is considerably larger. Further, by analysis of outcome, efforts are undertaken to reduce loss and enhance accuracy.

Main Effect Plot: Fig. 5 shows the Main Effect Plot for the adjustment of six hyperparameters. The main effect graphs show how each factor affects the sys-
tem’s overall performance. ‘Main effect’ is defined as when different degrees of a parameter have varying effects on performance. When the line is horizontal, it signifies that the characteristic average is the same across all variants of that hyperparameter. If the plot is not horizontal, and changes in the factor’s values affect the characteristic differently, there is a significant influence [12]. The major effect plot of test and validation accuracy in Fig. 5 is used to determine the best set of values for each factor. The element with the greatest fluctuation has the greatest effect on the system response, and hence has Rank 1 and so on, according to the ranks of main effect analysis. The optimizer and loss function have the largest impact on system performance, while the type of activation function has the least.

![Main Effect Plot and Main Effect Analysis from Minitab Tool.](image)

Fig. 5. Main Effect Plot and Main Effect Analysis from Minitab Tool.

4.1 Optimized Sequential CNN Model

Taking into account the hyperparameters listed in Table 1, the proposed values of parameters on the basis of Taguchi analysis are selected as shown in the main effect plot to maximize accuracy in Fig. 5. The number of CNN layers is 10, image size is [100x100], Activation function is Relu6, loss function is squared hinge, optimizer is adam, filter size [3x3], filters in each layer are [32, 32, 32, 64, 64, 64, 128, 128, 256, 256]. Proposed sequential CNN architecture is designed and confirmation run is performed taking into consideration these parameter and summarized in Table 3.

5 Conclusion

Automatic defect detection systems have proven to be more effective than manual inspection procedures in quality control. The goal of this work is to use
Table 3. Proposed Sequential CNN Architecture.

| Layer       | Type      | Output Shape  | No. of Parameters |
|-------------|-----------|---------------|-------------------|
| conv_1      | 2D, Conv  | (100, 100, 32)| 416               |
| conv_2      | 2D, Conv  | (100, 100, 32)| 4128              |
| conv_3      | 2D, Conv  | (100, 100, 32)| 4128              |
| max_pooling_1 | Pooling, max | (50, 50, 32) | 0                 |
| conv_4      | 2D, Conv  | (50, 50, 64)  | 18496             |
| conv_5      | 2D, Conv  | (50, 50, 64)  | 36928             |
| conv_6      | 2D, Conv  | (50, 50, 64)  | 36928             |
| max_pooling_1 | Pooling, max | (25, 25, 64) | 0                 |
| conv2d_7    | 2D, Conv  | (25, 25, 128) | 73856             |
| conv2d_8    | 2D, Conv  | (25, 25, 128) | 147584            |
| max_pooling_3 | Pooling    | (12, 12, 128) | 0                 |
| conv2d_9    | 2D, Conv  | (12, 12, 256) | 295168            |
| conv2d_10   | 2D, Conv  | (12, 12, 256) | 590080            |
| max_pooling_4 | Pooling, max | (6, 6, 256)  | 0                 |
| flatten_1   | Flatten   | (9216)        | 0                 |
| dense_1     | Dense     | (1)           | 9217              |

Total parameters: 1,216,929
Trainable parameters: 1,216,929
Non-trainable parameters: 0
No. of CNN Layers: 10
No. of Filters in each Layer: [32, 32, 32, 64, 64, 64, 128, 128, 256, 256]
Activation Function: ReLU6
Loss Function: Squared Hinge
Optimizer: Adaptive Moment Optimizer (adam)
Batch Size: 32
Filter size in each layer: [3x3]
Classifier: Binary Support Vector Machine

Fig. 6. Comparison of Results for Proposed Design.
Taguchi-based design of trials and analysis to create a robust autonomous system for visual inspection. A dataset of pictures of nut surface defects is developed and used. A sequential CNN architecture is created using Taguchi design of experiments and analysis. The findings suggest that choosing the right hyperparameters is crucial for attaining low loss values and higher accuracy in a specific application. Training accuracy is 98.69%, training loss is 0.0449, validation loss is 0.2794, and validation accuracy is 96.3% in this study. System resilience is seen with consistent training and validation outcomes, that is low loss and high accuracy are achieved.

In future work, more comprehensive study will be carried out taking into various categories of defects.

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