The Scientific Temper (2023) Vol. 14 (1): 172-177
Doi: 10.58414/SCIENTIFICTEMPER.2023.14.1.20
E-ISSN: 2231-6396, ISSN: 0976-8653
https://scientifictemper.com/

RESEARCH ARTICLE

Classification of weld defects using machine vision using convolutional neural network

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Abstract
Welding is an important aspect in commercial use of almost every industry. Because weld flaws can cause irregularities or inconsistencies during welding process, welding quality control is a critical step in ensuring the product's quality and overall longevity. This study focuses on recognizing contamination defects, lack of fusion defects, or if the weld belongs to the good weld category among the defects that occur during the welding process. This category categorization is carried out for the Convolutional Neural Network (CNN) algorithm and the accuracy metric is obtained to evaluate the efficiency of the algorithm for the 3 – class dataset. According to this research, the pure CNN approach gave an accuracy result of 96.1%.

Keywords: Accuracy, Convolutional Neural Network, Welding quality, Weld defects.

Introduction
In every product production process, inspection and quality control are critical. The human inspection approach was used in past decades. Monitoring occupations are considered time-consuming and monotonous by humans. According to studies, manual inspection is predicted to be responsible for 10% or more of total labor expenses on manufactured products. As a result, automation was a must. Despite the fact that technology improvements have resulted in increased automation of industrial processes, concerns with monitoring and quality control have yet to be fully addressed. Global manufacturing markets have been striving to develop more cost-effective, higher-quality items. Welding flaws are also an unavoidable component of the process in the welding industry. The presence of a weld flaw in the metal has an impact on the welded material's quality. The term "weld defect" refers to any imperfections or inconsistencies on the weld's surface. Non-destructive testing (NDT) are used to track several sorts of weld defects (Deepak *et al.*, 2021).

The high-quality welding procedure known as Tungsten Inert Gas welding (TIG welding) was used to generate the database with three classes. As illustrated in Figure 1, TIG welding is a type of arc welding that employs an inert tungsten electrode to make a weld. Gas Tungsten Arc Welding (GTAW) is another name for it. During the TIG welding procvess, an arc is created between the workpiece metal and a pointy tungsten electrode in an inert atmosphere of helium or argon. The tiny powerful arc created by the pointed electrode is ideal for producing high-quality and precise welding. Because electrode consumption does not occur during welding, there is no need to balance the heat input from the arc. Also, Fande, Taiwade & Raut (2022) and Devakumar & Jabaraj (2014) provide additional information about TIG Welding.

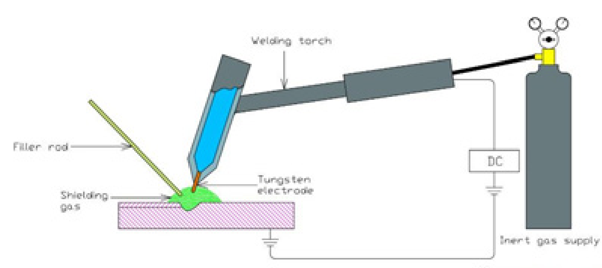

Figure 1: TIG Welding

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How to cite this article: Kanthalakshmi, S., Nikitha M. S., Pradeepa G. (2023). Classification of weld defects using machine vision using convolutional neural network. The Scientific Temper, **14**(1):172-177

Doi: 10.58414/SCIENTIFICTEMPER.2023.14.1.20

Source of support: Nil

Conflict of interest: None.

Received: 11/01/2023 **Accepted:** 12/02/2023 **Published** : 25/03/2023

There are a variety of TIG welding problems. However, contamination defects and incomplete fusion defects are the most common. Contamination can develop as a result of tainted metal or electrodes used in the welding process or as a result of an uneven shield gas flow. Lack of fusion can be caused by a slow welding speed or a replacement leading edge of the arc that is moved away from the puddle. For the gathering of the three class database, a dataset including both of these weld flaws and a good weld was conducted for TIG welding using the Aluminium 5083 metal Alloy.

Figure 2 depicts the three types of weld faults that make up the dataset to be classified. Our research focuses on visual testing, which reliably and consistently finds flaws in aluminum 5083 weldments using the TIG welding process. Visual testing is focused in order to minimize manual mistakes and save time when executing for a large number of datasets. By processing the dataset through the convolutional neural network (CNN) algorithm, locating and categorizing weld defects in metal is being done. This dataset is separated as testing and training data. The training data is divided into batches using data augmentation, and each batch is being put into the algorithm to train the neural network to gain the needed weld image attributes for classification. The accuracy metric is used to assess and compare the three methods. This comparison is helpful in determining which algorithm may be utilised for commercial applications to enhance efficiency and extend the life of the weld product.

Related Works

This section lists the studies that were conducted in conjunction with this project. The advantages of connecting two different metals are outlined in paper (Zhang *et al.*, 2020). It also presents an overview of recent research on TIG welding in joining metals based on structural, property, and performance aspects. This research analyzed the difficulties in welding dissimilar metals due to their differences in metallurgical, physical, and chemical characteristics by reviewing a total of 29 studies. The inspection method for detecting weld faults has shown to be important in order to overcome issues such as picture inaccuracy and noise, poor contrast, and non-uniform lighting. These issues were solved in the paper by Chu & Wang (2016) by developing a novel machine vision-based inspection system for detecting and classifying weld flaws in MIG (Metal Inert Gas) welding. The nature of electrical transients created by arc welding, i.e. the magnitude and length of the transient induced in propulsion lines and conveyed to interface circuits, is discussed by Bodeau (2018). Various mitigation approaches for TIG welding have been presented for various circuit types in order to mitigate or eliminate potential damage. The total number of pixels is extracted as the main parameter using the grey interval derived from the Region of Interest (ROI). The pixel ratio technique is used to remove background noise, which helps to increase the signal-to-noise ratio (Zhang & Wen, 2016).

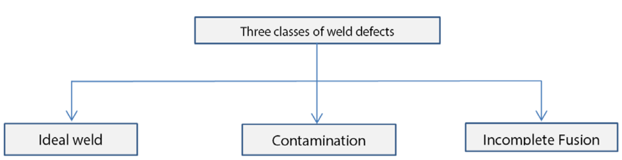


Figure 2: Three classes of weld defects

In a paper by Bacioiu *et al.* (2019), a new dataset of 33,254 photos depicting the TIG (Tungsten Inert Gas) welding process of Aluminium 5083 metal with increased contrast was created using a High Dynamic Range (HDR) camera. This dataset contains five distinct welding flaws as well as a good weld. This research introduces an ANN (Artificial Neural Network) paradigm for accurately categorizing welding defects. The accuracy of a Deep Neural Network is increased by using a big dataset, yet, a limited dataset produces less accurate results. This drawback can be solved by adopting transfer learning approaches that use deep CNN to pretrain the dataset (Sekhar, Sharma, & Shah, 2022). A manual dataset of 940 weld fault photos is pre-trained using VGG16 and ResNet50 CNNs, and then processed via machine learning models, including Support Vector Machine (SVM), Logistic Regression, and Random Forest, which conduct extraction and classification. The CCD camera may also produce a dataset, as described in the article (Patil & Reddy, 2021). The co-occurrence matrix and grey absolute histogram are utilised in this study to extract properties such as energy, homogeneity, correlation, and contrast. Weld flaws are classified as excellent weld, excess weld, or inadequate weld using the (SVM, a machine learning approach. Sun *et al.* (2019) proposed a method for identifying and classifying

Table 1: Dataset Classification

Welding Types	*No. of images in each phase*		*Total no. of images*
	Training	*Testing*	
Good Weld	882	220	1102
Contamination Weld Defect	728	181	909
Incomplete Fusion Weld Defect	807	201	1008
Total			3019

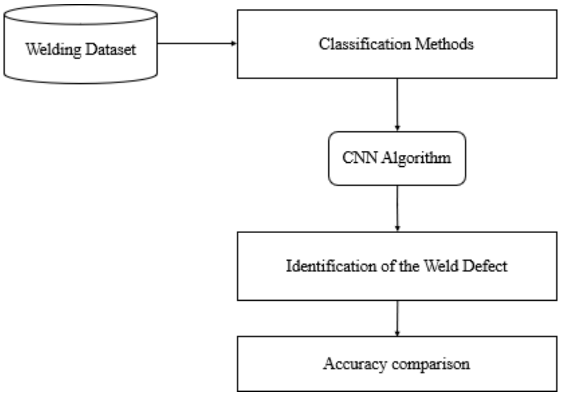


Figure 3: Overview of proposed work

weld flaws in the regions of thin-walled metal canisters. The feature extraction from the dataset is done using a subtraction approach based on gaussian mixture models, which has a classification accuracy of roughly 95%. Dong, Taylor, & Cootes (2018) merged the CNN and random forest. The CNN handles the feature extraction method, which extracts the weld fault zone from the dataset image. To determine the type of weld fault and classify it, the retrieved characteristics are fed into a random forest algorithm. The random forest algorithm was also regarded as one of the classification approaches to identify and detect the kind of weld flaw to accomplish Non-destructive welding (Kulkarni, *et al.*, 2022). The CNN and SVM classifier based on the radial basis function (RBF) are used to identify aggressive and benign breast cancer. Using RBF in an SVM allows for more freedom in tweaking the kernel width and aids in data dimension fitting (Desai & Shah, 2021). For the dataset utilized, this hybridization yielded more robust findings. Weld flaws such as incomplete fusion, burn-through, and whether it's a good weld are identified using the random forest algorithm and the J48 method, and the results are compared, with the findings showing that the random forest technique is more efficient. SVM and CNN algorithms [15] can also hybridize (Bansode,Dildar & GS, 2022). CNN is predominantly utilized for classification in this article. The

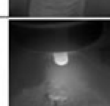
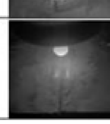
Welding type	Image
Good Weld	
Contamination Weld Defect	
Incomplete Fusion Defect	

Table 2: Samples of Welding Images

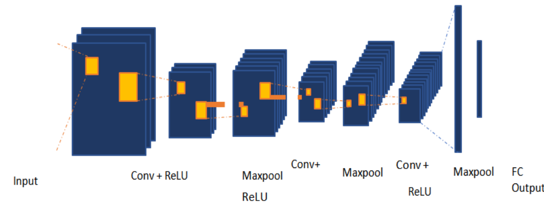


Figure 4: CNN Architecture

Support Vector Machine takes up the process of isolating and detecting the faulty area. For pre-processing, morphological filtration is used, which helps decrease computing costs and the risk of false alarm. CLAHE (Contrast-Limited Adaptive Histogram Equalization) is used as a histogram equalization approach to reduce the noise component.

Proposed Methods

This research uses the TIG welding dataset to test multiple classification strategies and determine the most effective model for classification using accuracy as a parameter. CNN, a popular image classification approach, is used to classify welding flaws. Figure 3 depicts a high-level summary of the proposed effort.

Dataset

In total, 3019 images are utilised in the TIG welding real-time dataset for classification. A good weld, an lack of fusion weld defect, and a contaminated weld defect are all included in the dataset. The images are in the .png format and have a 800 × 974 pixels resolution. For the training and testing phase, each dataset class is divided into two groups. The categorization of the dataset to be utilized is shown in Table 1. The samples of each type of welding picture, which are good weld, contaminated welding defect, and incomplete fusion defect, are tabulated in Table 2. The dataset was produced using a hardware setup that included a CCD camera that captured the welding operation in real time.

Convolutional Neural Network

Convolutional neural networks are made up of several layers of synthetic neurons. Similar to their biological counterparts,

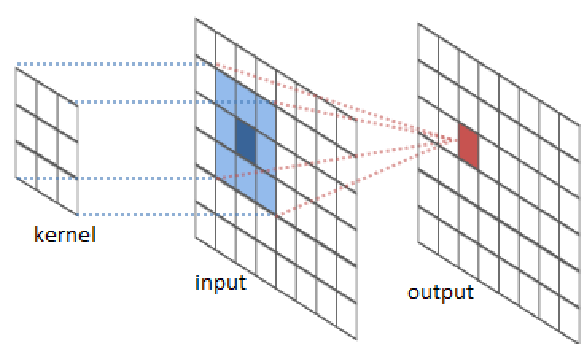


Figure 5: The kernel stride across input feature map to compute the convolved output feature matrix

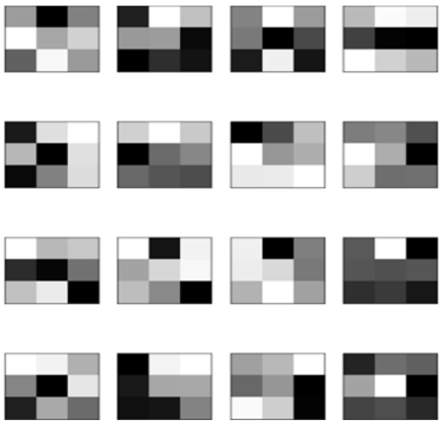


Figure 6: Filter Visualization of the first convolutional layer

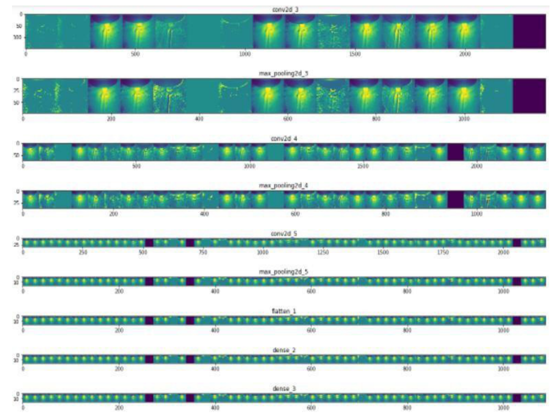


Figure 7: Feature Visualization

artificial neurons are computational models that evaluate the weighted sum of numerous inputs and produce an activation value as an output. Because CNN includes the feature extraction stage, classic approaches do not require a separate pre-processing phase for an image. In order to infer the objects present in a picture, the original pixel of the image data is provided as the input in the form of arrays. The revelation that a CNN was helpful in extracting higher-level interpretations from the image was a breakthrough in creating models for image categorization. Rather than pre-processing the data to extract features such as textures and forms, a CNN uses the image's original resolution data as input and learns the feature extraction to determine the object they represent. To begin, the CNN is given an input feature map, a three-dimensional matrix whose first two dimensions represent the picture length and width in pixels. The third dimension is 3 in length, corresponding to the 3 channel colour i.e red, green and blue (RGB). CNN architecture is illustrated in Figure 4.

The input layer then processes the 800 x 974 pixel welding picture to produce a resized image of 150 x 150 pixel image in order to scale all of the photos to a consistent size before processing through the neural network and to create formatted data. Following that are the hidden layers, which aid in the extraction of information from the image. The layers are as follows:

Convolutional Layer

The output feature map, is created by extracting tiles from the input feature map and applying kernel or filters to them to generate additional features. Filters contains differ in size from the input feature map. The size of the tiles extracted and the number of filters applied are the two factors that helps in determining the convolutions. During a convolution, the kernel essentially travels horizontally and vertically over the input grid, to extract the matching tile, one pixel at a time as shown in Figure 5.

The CNN conducts entity-wise multiplication of the filter and the input tile for each filter-tile combination, it adds all the elements of the resultant matrices to yield a specific value. Each of these values results in the convolved output feature matrix. The CNN helps to learn the values for the filter matrix that allow it to extract features that are required from the input feature map during training. F However, because filters account for the vast bulk of the

CNN's resources and training time grows if more filters are applied. Furthermore, because each new filter added to the network adds less incremental advantage than the previous one, engineers strive to build networks with the fewest possible filters to extract the information required for effective picture categorization.

Pooling Layers

Following ReLU, the CNN process the convolved feature to minimize the size of the feature map while keeping the most relevant feature characteristics. Max pooling is a typical method employed in this procedure. Max pooling works in the same way as convolution does. A slider is used to stride across the map to extract the convolved tiles of a certain size. The highest value is exported to a new attribute map for each tile, while deleting other values.

Fully Connected Layer

At the end, one or more fully connected layers are found in a convolutional neural network. Their task is to classify data using the characteristics collected by the convolutions. FC layers often use a softmax activation function to generate a probability ranging from 0 to 1 attempting to predict. The equation defines the softmax activation function

$$Y' = \frac{e^{z}}{\sum_{r=1}^{n} e^{z_r}}$$

where n is the number of classes and z denotes the output value for the current batch after the convolution neural network has processed it.

The CNN architecture implemented in this paper is described below :

- INPUT: 150 x 150 x 3
- CONV: 3 x 3 size, 16 filters, 1 stride
- ReLU: max (0, x)
- MAX-POOL: 2 x 2 window, 1 stride
- CONV: 3 x 3 size, 32 filters, 1 stride
- ReLU: max (0, x)
- MAX-POOL: 2 x 2 window, 1 stride
- CONV: 3 x 3 size, 64 filters, 1 stride
- ReLU: max (0, x)
- MAX-POOL: 2 x 2 window, 1 stride
- FC: 512 hidden neurons with ReLU activation function
- OUTPUT: 3 Output classes with softmax activation function

Experimental Results and Discussions

The four factors of current, voltage, gas flow rate, and arc weld travel speed substantially influence the weld qualities, as shown in Table 1. Changes in these factors can have a broad variety of effects on the welding process. This welding process, which features errors induced by variations in the baseline values, has been used as a dataset for the CNN algorithm.

CNN

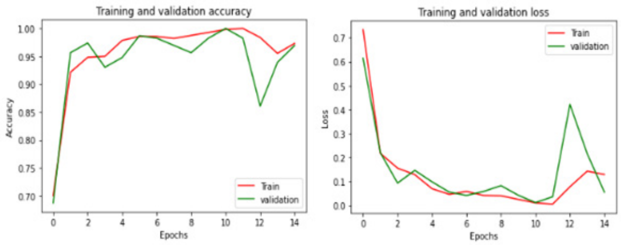
The most prevalent image classification technique is the convolutional neural network. The flow from directory function may be used to get the TIG welding dataset from directories. It generates batches of enhanced normalized datasets with three classes of 80% training and 20% testing pictures, which are fed into the CNN model as described in Table 3, and the output is generated.

The shape or pixel of each layer is depicted in Table 3, along with the number of parameters utilised in each. In this model, three network layers are employed to generate the output: an input layer, a convolutional layer with maximum pooling, and dense and flattened layers. The scaled picture of dimension is placed in the input layer (150 x 150 x 3). The convolutional layer modifies the picture for the set number of filters, while the max pooling layer shrinks the image's length and breadth. There are three convolutional layers in total. The first layer has 16 filters, but the second and third layers contain 32 and 64 filters, respectively, since high level characteristics are retrieved from them. The image is flattened into a 1- dimensional representation with all of the major details intact (17x17x64 = 18496). The dense layer, also known as the fully linked layer, has 512 hidden units, but the output layer only has one.

Figure 6 depicts the first convolutional layer, which employs 16 filters. This filter visualization generates 16 pictures in total, each representing one of the 16 filters in four rows and columns. Dark squares indicate tiny weights with suppressive values, whereas bright squares represent excitatory weights with big values. Filter initialization is done at random using a normal distribution.

Filters that operate as feature detectors are applied to the input image and the feature map's prior layers. Figure 7 depicts the feature filtering procedure as well as the internal representation of the feature extraction process in each layer. The first convolutional layer is represented by conv2d_3 and max pooling2d_3 in Figure 7, followed by max pooling, which contains 16 filters in both rows. Similarly, the layers conv2d_4, max pooling2d_4 and conv2d_5, max pooling 2d_5 represent the second and third convolutional layers, respectively, with 32 and 64 filters. The output is then obtained by following the flatten and dense layers. It is clear that the welding area geometry, i.e. the height and breadth of the welding region, is the influencingfactor in determining the classification output.

The curve in Figure 8 was created using categorical cross entropy as the loss function and accuracy metric across 15 epochs. Figure 8 (a) depicts the graph's fluctuation throughout 15 epochs, with the validation accuracy reaching 96.1 percent in the fifteenth epoch. Similarly, in the instance of Figure 8 (b), the validation loss was close to 5%.



(a) (b)

Figure 8: (a) Accuracy curve for training and validation (b) Loss function curve for training and validation

Conclusion

This study successfully classifies the TIG welding dataset using three algorithms implemented in Jupyter notebook IDE using python language. It can be observed that the pure CNN model gave an accuracy of 96.1% in classifying the 3-class real-time welding dataset. Thus, the accuracy is used as a metric to predict the classification algorithm for the welding dataset. The real–time dataset was classified into 80% training and 20% testing and was passed to the data augmentation process. This concept might be improved by combining it with a camera that can offer real-time welding input to industries that use TIG or other welding methods. This will be a very powerful alternative for sectors that use automated welding, since it will save manpower and costs significantly.

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