Use of ResNet modelling for TIG weld feature digitization and correlation – A technique for AI based welding system

Ramesh Kuppuswamy[1*], Keanu Calo[1], J. Ramkumar[2]

[1]*University of Cape Town, South Africa*
[2]*Indian Institute of Technology, Kanpur, India*

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ABSTRACT

TIG Welding is being practiced in the manufacturing industry and it demands highly skilled labour. Artificial Intelligence (AI) is developing rapidly as researchers are constantly finding new ways in which intelligent machines can add value to their industry. An AI-based welding system stands to add value by increasing production rates, improving safety, and decreasing the human input required. Weld monitoring is a key activity in the TIG welding process and successful use of AI system will enable failure prediction and the proactive corrective actions. The aim of this project is to explore, test, and compare ResNet modelling based machine learning algorithms and examine their ability to monitor welds. In this project the weld monitoring process includes collecting images of weld joint for weld feature digitization. Also, the study enables predicting whether the weld shows good quality, contamination, burn through, misalignment, lack of fusion, or lack of penetration through a ResNet modelling based image analysis.

1. Introduction

Tungsten inert gas (TIG) welding is a complex process that is high in demand in the manufacturing industry (Fande et al., 2022). In the advent of big data and industry 4.0, there have been efforts made to detect weld defects in TIG welding and various other welding processes (Gyasi et al., 2019). Should these efforts lead to successful implementation of weld automation in industry, the TIG welding process will overcome the various problems consequent of human labour. TIG welding is a practice which relies on a worker's experience and skill to adequately judge the process through surface level inspection. Workers are expected to make educated decisions about a particular job such that they may adequately meet the required process parameters. The process parameters of TIG welding have a direct influence on the quality of the product, making the parameter choice a key activity. Machine learning algorithms have been able to mimic human cognitive function to reproduce human abilities such as learning, image classification, and feature recognition. This manuscript unveils the output of ResNet-50 and ResNet-18 modelling using the MATLAB coding. The neural networks have been trained to perform feature extraction from a training dataset as well as perform feature correlation on a verification dataset. In this way, the neural networks were able to classify a given weld image as a good weld or as a particular defective weld from a list of common TIG weld defects. The ResNet model was designed to make predictions based solely on photos of the TIG welding process on 5083 aluminium using an HDR camera.

2. Past Research Findings

Several past studies were noted in the fields of artificial intelligence and welding sciences individually; however, few researchers have investigated that merge the two fields to produce intelligent welding systems. Some of the noticeable past works are.

A study Kesse et al. (2020) takes a unique approach in designing a system that serves to aid the welder in the selection of welding parameters (current, arc length, welding speed) by outputting the predicted resultant bead width, based in the welder's chosen input parameters.

*Corresponding author
E-mail: Ramesh.kuppuswamy@uct.ac.za

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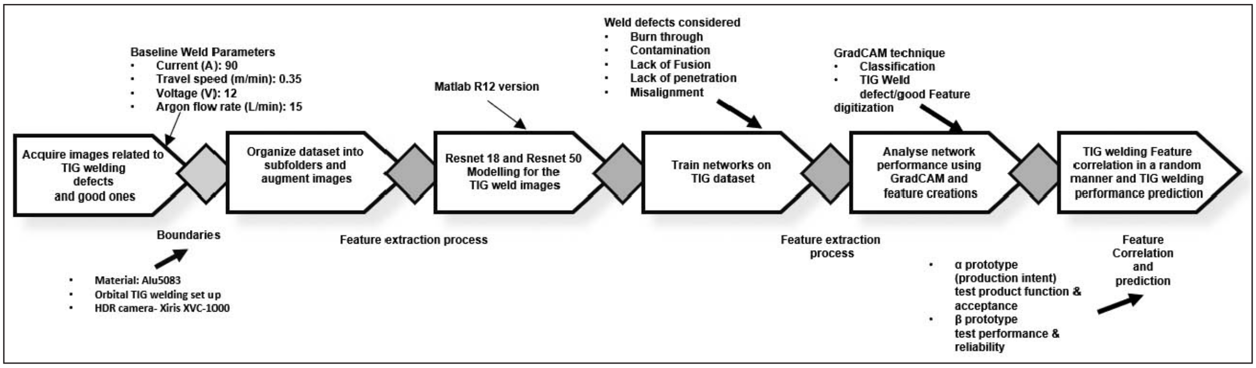

Fig. 1. Sequence of activities followed for ResNet-50 & Resnet-8 modelling for AI based TIG welding process.

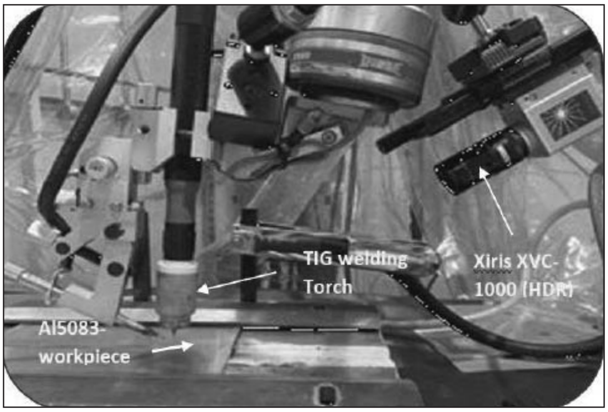

Fig. 2. TIG welding experiments conducted on DINSE TIG welding system @ Atlantis Castings, South Africa.

A hybrid fuzzy logic/DNN algorithm was used to make predictions. Fuzzy logic is non-binary and provides a spectrum of truths (Plato.stanford.edu, 2022). Another group of researchers Das et al. (2017) take a similar approach but with an improvement with the development of a model that can predict welding parameters based on a desired weld penetration and vice versa whereas the hybrid Fuzzy logic/DNN model is only able to predict weld bead width based on welding parameters. Algorithms used for prediction include BPNN, GANN, PSONN, PSORNN, NBARNN with achieved prediction absolute deviations of less than 9% for weld penetration and less than 12% for weld parameters. While this study adds value to the field of study, the proposed system is still largely human reliant.

A key aspect of the welding process is non-destructive testing for detection and identification of weld defects. Researchers Xia et al. (2020) present an image-based defect sensing system for keyhole TIG welding. An image classification algorithm (ResNet with 18 convolutional layers) is trained to classify a given image as either a good weld, or one of 5 various defected weld types with an overall accuracy of 98%. Another group of researchers Bacioiu et al. (2019) take a largely similar approach in weld defect detection using TIG welding on aluminium 5083. The image classification is performed using both a convolutional neural network (CNN), and a Fully convolution network (FCN). The researchers find that the CNN exceeds the FCN in prediction accuracy by 18% on average. This suggests that a CNN may be superior for image classification.

Therefore, this study was aimed to build AI based TIG welding platform using a hybrid deep learning technique. The weld process data collected would be analysed using convolutional neural networks (CNN).

3. Methodology

Shown in Fig.1 is the sequence of activities followed in this project.

The training of the CNN is performed with the TIG Aluminium 5083 dataset created after extensive experiments using a TIG welding set up (See Fig. 2). The TIG welding process involves the use of a non-consumable tungsten electrode, Argon shielding gas, and an electric arc as a heat source to melt the weld pool. Welding is performed on 2 mm thick Aluminium 5083 grade at a groove angle of 90 degrees. The weld parameters used in the experiments and their behaviour are given in Table 1. Table 2 list down the number of images used for training and validations. An HDR camera (XRIS XVC1000) was set up to capture images @ 55 frames per second. The image captured was stored as a 3-Dimensional array with each dimension representing red, green, or blue light, with each member of the array representing a pixel in the image with a value ranging from 0-255, indicating the intensity of light. The ResNet-50 model takes images of size 224x224x3, being RGB images that are 224 pixels high by 224 pixels

Table 1
TIG welding parameters used for welding of Al5083.

TIG Weld Feature	Current (A)	Welding Speed (CM/ MIN)	Constant Conditions
Good Weld	70~100	20~50	Voltage12 V; Argon flow rate 15 L/min
Burn Through	100	10~15	
Contamination	60~100	15~50	
Lack of Fusion	40~60	25~30	
Misalignment	50~80	20~50	
Lack of Penetration	60~80	25~30	

Table 2
Number of images used for training and validations.

Label	Train Value (number of images)	Resnet 18 (number of images)	Resnet 50 (number of images)
Good weld	1249	200	199
Contamination speed	2461	199	200
Lack of Fusion	1611	200	200
Burn Through	1729	200	200
Lack of Penetration	1789	200	200
Misalignment	1567	200	200

wide, so the initial dataset is augmented to fit this size. The MATLAB network training function also requires that the data is stored in a specific manner within a folder for learning. The dataset included is a JavaScript Object Notation (JSON) file that contains the name of every image as well as its classification. Python script was used to move the image dataset to the correct subfolder by comparing its name to the JSON file. Convolutional layer was used for weld feature extraction, and it was observed that the initial layers extract low-level features such as edges of the weld zone and colour gradients that arise from the heat affected zone (HAZ) and as the image progresses through each layer, the layers extract more complex features. ResNet is a deep Residual Network that overcomes the difficulties in training networks with many convolutional layers for image classification and the number that follows ResNet (ResNet-50) implies that it comprises 50 hidden layers. The hidden layers enable image classification. Images are read by the algorithm as an array of digits, with each element of the array being a value between 0-255, representing the intensity of light. The convolutional operation involves an element-wise multiplication of a portion of the input matrix (image) with another square matrix, known as the filter or kernel. Once the convolved matrix has been calculated, an element wise summation is performed on it, outputting a single digit. The filter shifts to the right as it performs the convolutions by a certain amount known as the stride. This is repeated until the entire image has been traversed. Finally, every element of the convolved matrix is summated to produce one scalar value. The kernel is applied across the entire image until a new matrix of these scalar values is produced. The network is made up of multiple convolutional layers that each apply a filter (convolution operation) to the image in an attempt to extract defining features of a class of image. These filters are random at first, but they are fine-tuned by the algorithm until they can effectively extract important features. The building of feature extraction engine requires no input from a human.

A proper determination of kernel size should depend on the relative size of the object (or the region) of interest with respect to the image size. One unwritten rule of kernel size is that, with layer propagation, the kernel size should become smaller and smaller. With the development of deep learning, the kernel size is preferred to be small to fully capture the local information. Typically, kernel size is set through trial-and-error. The difference is that the kernels applied, which are fixed/designed artificially in traditional image processing are learnable and trained from training data in CNNs. With the convolutional layers going deeper, the features are more and more abstract and related to the final target. The initial layers extract low-level features such as edges of the weld zone and colour gradients that arise from the heat affected zone (HAZ) and as the image progresses through each layer, the layers extract more complex features. Thus, an architecture with a high number of layers will be capable of identifying more complicated features. Large networks run the risk of overfitting which reduces generalisation of the network. It is difficult to know exactly how many layers are too much, so the best way to find out is with experimentation. It would thus be ideal to test

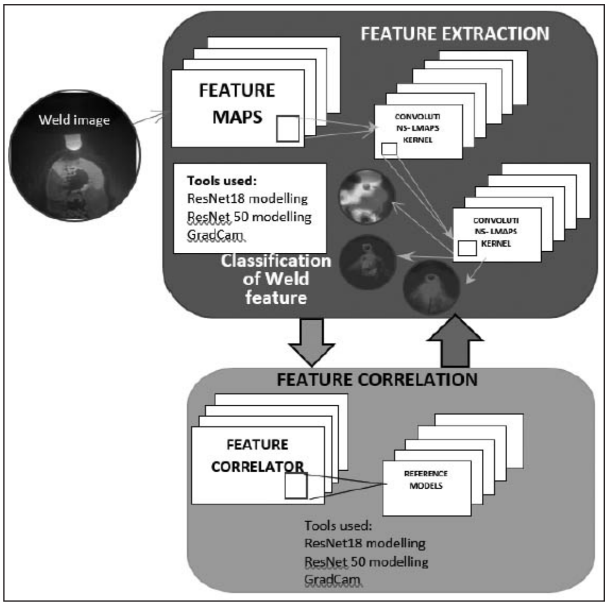

Fig. 3. Framework of image processing method for weld feature extraction and correlation.

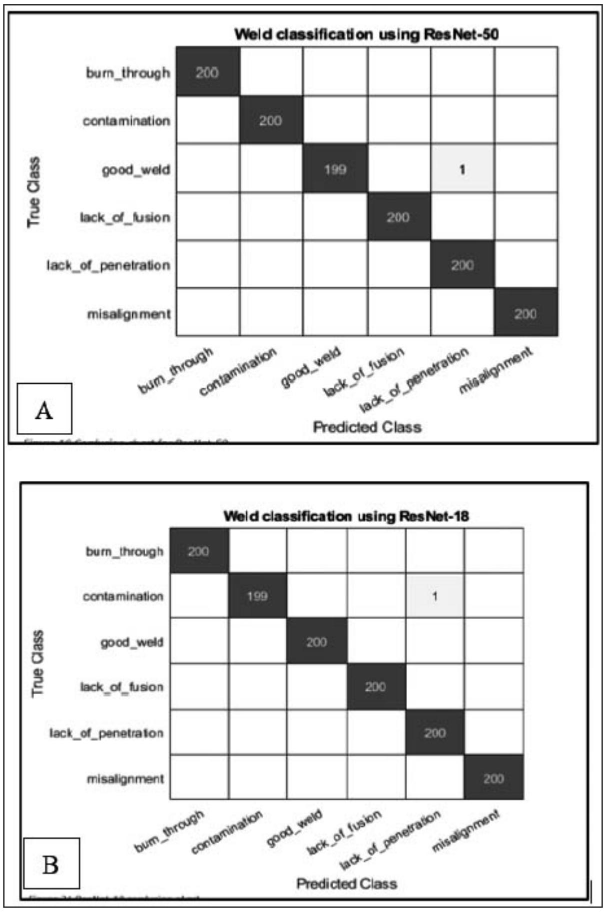

Fig. 4. Confusion chart created using (A) ResNet 50 and (B) Reset 18 modelling.

the performance of the model with a varied number of layers. For this reason, the ResNet-18 architecture was also used to train and test before comparing the performance of an 18-layer deep network against a 50-layer deep network. The parameters that need to be determined to train the ResNet-50 model includes number of neurons in the output layer, learning rate, momentum constant, maximum number of iterations and bias value. A guided gradient-class activation mapping (Grad-CAM) was used to produce a heat map highlighting which regions of the image the network considers important for prediction.

Shown in Fig. 3 is how the image processing is done for weld feature extractions and correlations.

4. Results and Discussion

The goal of network training is to produce a network that has successfully extracted the defining features for each TIG weld feature and to use the convolutional filters to correlate these features with any given image and predict which weld feature it belongs to. A deeper network was able to extract more complex features but also runs the risk of overfitting to the training data. In order to find out how deep the network is required to be, the performance of the ResNet-50 model is compared to a shallower ResNet-18 model. Both models were trained using 1000 images from each class and validation was performed with 200 images per class. The ResNet-50 model completed training in 257 minutes 30 seconds with a final validation accuracy of 99.75% and validation loss of 0.0144. The ResNet-18 model completed training in 106 minutes and 49 seconds with a final validation accuracy of 99.67% and validation loss of 0.0081. The ResNet-50 model shows a 0.8% improvement in prediction accuracy but a deficit of 0.0063 in validation loss. Based on these results, 18 layers preferred for training due to its shorter training time and superior loss. With training completed and both networks ready to classify a test dataset, various analysis tools can be used to investigate how each model performs. Shown in Fig. 4A and Fig. 4B is the confusion chart created using ResNet 50 and Reset 18 modelling. Confusion charts are a fast way to present where the model is misclassifying images, showing the number of images correctly and incorrectly classified.

ResNet-50 predicts the classes of images in the test dataset almost perfectly, with exception to an image of class “good weld” being incorrectly predicted as “lack of penetration”. The Grad-CAM algorithm was implemented to gather insight into how the network is making predictions so that it

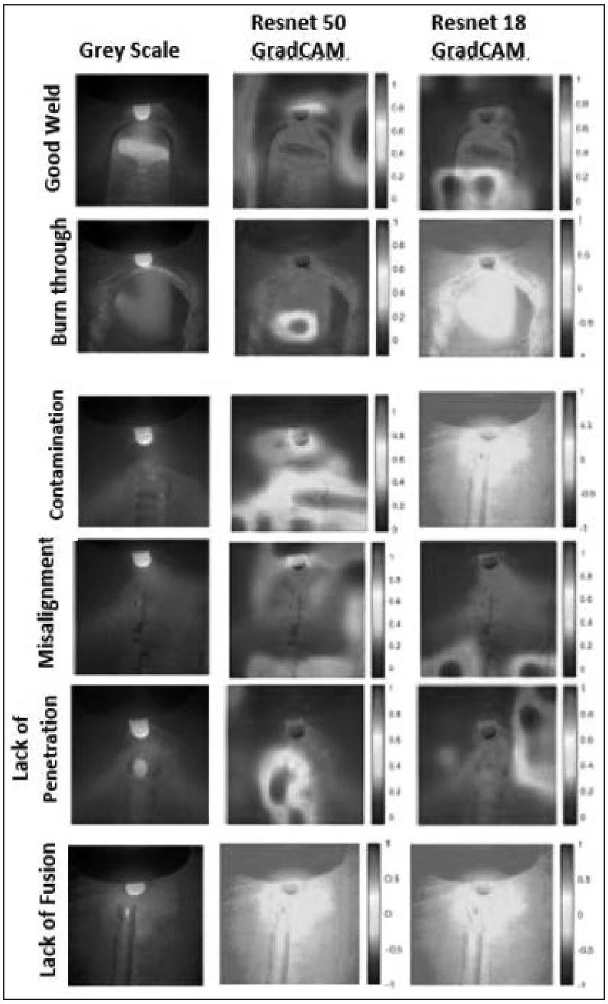

Fig. 5. Comparisons of TIG weld images using grey scale, ResNet-50 and ResNet-18 modelling.

can be postulated why a misclassification may occur. The Grad-CAM visualisation of each class of image is shown in Fig. 5. Upon inspection of any image in the class good weld to defective weld there are few distinguishing factors between the two classes and gives us an opportunity to extract a digital feature. It was noted that grey scale images offer less clarity of information than the Grad-CAM images as the GRADCAM is featured with heat map contents. Shown in Fig. 5 is the Grad-CAM heat maps which reveal that the network is focusing on the features for the good weld and defective weld. The "good weld" class was characterised by features on the left and right sides of the collected image. The images are a representative of images from each class come from the extensive experiments, deigned to create the desired weld features. Each image share details of the base metals, weldment, light reflections which was used for identification of the features. This is an indication that the model is aptly fitted with the training data and hence the classification of images from this specific dataset is within the acceptable limits. By visual inspection it can be seen how the classes "contamination" and "lack of fusion" may be confused as the two classes of images are visually similar in grey scale. However, Grad-CAM images shows the additional information and enable to better segregate the images and adds value to the digital feature collections. In addition to the visual similarities, the Grad-CAM explanation shows that the network is focusing on similar parts of the images (upper right corner) that do not coincide with the greyscale weld site. As with the ResNet-50 model, the ResNet-18 model appears to be less informative and, in some cases, the ResNet-18 images gives information that are unrelated to the weld quality. Occasionally it was noted that the problem of overfitting does exist in Grad CAM algorithm for both a 50 layer and 18-layer deep CNN. Therefore, several additional ultrasonic examinations were done to counter check the images, but the results were not covered in this manuscript. The Grad CAM heat map images do contain scale from 0-1 (one being most prominent and zero being not at all), the most important features that the CNN is using to digitally define each class.

- **Good weld**

The ResNet-18 and ResNet-50 model evidently identify features of a good weld as the heat map is heavily focused on the weldment area. However, Resnet 50 model captures additional information that defines good weld. A good TIG weld for welding 2 mm Alu5083 sheet did consume current 70~100 A, Travel speed 200~500 mm/min, Voltage 12 V and Argon flow rate 15 L/min. The digital features average out the pixels value with a 5x5 filter to flatten the colour gradients, and classify the image as "good weld" if there is a lighter rectangular region of pixels (pixels with lower values) of the same value in between two darker regions which is the base metal).

- **Burn through**

The weld defect burn through occurs when excessive penetration is taking place. It typically happens when the arc current or voltage is too high and/or the travel speed is too low, resulting in the heat added exceeding the heat required for melting and fusion. The specific heat input required ia TIG welding is given by the equation 1.

$$Specific\ heat\ input = \frac{Voltage\ x\ Ampherage}{Travel\ speed\ x\ Mass} \quad ....(1)$$

The heat map shows that the ResNet-50 model focuses on a region in the centre of where burn through has occurred, but not on the edges of the burn through, as hoped for. The green mask over the ResNet-18 heat map indicates that no features of the image in particular were learned by the model (green is associated with a value of 0) and hence appears to be less informative. Despite learning the incorrect features of the class, both models achieved prediction accuracies of over 98% in this class, meaning that the models are exceptional at predicting images of this class in this dataset exclusively, but may not be able to make accurate predictions of images of this class from outside this dataset. If this class were to be defined digitally, the steps involved would be to average out the value of the pixels with a 5x5 filter to flatten the colour gradients, and class the image as "burn through" if there is a darker rectangular region of pixels (pixels with a higher value) of the same value in between two lighter regions (the base metal).

- **Contamination**

Contamination is the presence of foreign or unwanted particles in or around the weld. These particles may include dust, oil, or metal shavings and most commonly reside on the surface of the base metals. Like the "burn through" class, the ResNet-18 model is not effectively identifying any features of the "contamination" class, as indicated by the green mask over the image in the heat map. However, the heat map for the ResNet-50 model shows that certain regions of the actual weld are being focused on, as suggested by the light red regions over the weld area. Still, there is a dark red region in the corner of the heat map, showing that the deeper model is learning features both related, and unrelated to the actual weld. This indicates that the ResNet-50 model may perform better at making predictions of images from outside the dataset than the shallower 18-layer model. The defining characteristics of this class was done by identifying foreign particles according to their pixel value. If there is a cluster of pixels that deviate from their surrounding pixels by more than 50%, that group of pixels than it was defined as contamination. If more than 20% of pixels in the image are identified as foreign particles, the image was classified as "contamination".

- **Misalignment**

Misalignment refers to when two base metals are not level with one another as they should be dimensionally. The heatmaps show that both models are focusing on the bottom of the image – unrelating to the details of the weld. This is the only case where it seems both the deep and shallower networks are focusing on similar regions of the image. This class of image was manually classified by averaging the pixel values with a 2x2 filter and searching for vertical lines of higher pixel values. If there is more than one misaligned line running up the middle of the image, the image may be classified as "misalignment."

- **Lack of penetration**

Lack of penetration refers to when the weld does not completely fill the joint. It occurs when the welding parameters such as arc current and voltage, or travel speed are not controlled properly and results in a weakened joint. The deeper ResNet-50 model more effectively extracts the defining features of this class. The heatmap shows that the 50-layer CNN focuses entirely on the weld details while the 18-layer CNN is focusing on details beside the weld. This suggests that the ResNet-50 model is more likely to have a better prediction accuracy for this class of image outside of the dataset it was trained on. This class can be defined digitally by averaging out the values of all pixels using a 5x5 filter size and classifying the image as "lack of penetration" if there is no change in gradient in the centre of the image, where the weld bead should be.

- **Lack of fusion**

Lack of fusion occurs when the weld does not properly fuse with the base metals. This can happen when the heat input is lower than the heat required for melting and fusion, due to too low a voltage or current, or too fast a travel speed. This relationship was given in the equation 1. The green mask over the images indicates that neither model is learning any specific feature of the "lack of fusion" class. It follows that the depth of the network may not be influencing the effectiveness of the CNN in this case, but other parameters of the CNN need adjustment so that both networks are able to accurately classify images of this class outside of this dataset. The characteristic feature of this class may be defined digitally by scanning through the image vertically, and classifying the weld as "lack of fusion" if there is a vertical matrix of pixels 50% darker than the surrounding pixels in the centre of the image.

5. Conclusion

This study demonstrates the application of artificial intelligence for TIG welding using a specially designed AI deep learning algorithm that is capable of receiving an image of a weld and predicting whether the weld is of the class good weld, burn through, contamination, lack of fusion, lack of penetration, or misalignment. The main conclusions are

- Implementation and modification ResNet-50 and ResNet-18 CNN models
- Acquisition and augmentation of a TIG on Aluminium 5083 dataset
- Training of both models using the augmented data
- Prediction accuracy of over 99% from both models

Despite the high prediction accuracies, the Grad-CAM algorithm appear to be useful if the persistent problem of overfitting is carefully attended to it.

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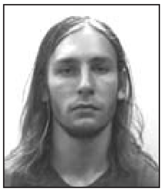
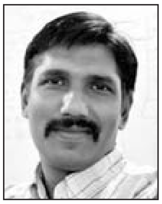
Dr. Ramesh Kuppuswamy is a Professor, Department of Mechanical Engineering, University of Cape Town, South Africa. He graduated and post graduated in Mechanical Engineering from Anna University, Chennai and IIT Madras respectively. He obtained Ph.D (Mechanical Engineering) from NTU, Singapore. He guided 126 Ph.D, M.Sc and B.Sc (Hons) students in advanced manufacturing particularly on grinding and polishing related processes. He is a author/ co-author for a 110 internal peer reviewed journal/conferences, book chapters and books. He is a NRF C2 rated research at South Africa.



Keanu Calo obtained his B.Sc Engineering degree in Mechanical Engineering from the University of Cape Town, focussing on intelligent manufacturing (AI in TIG welding in particular) in his final year project.
(E-mail: clxkea001@myuct.ac.za)



Dr. J. Ramkumar, Professor in the Department of Mechanical Engineering and Design Program at Indian Institute of Technology Kanpur, has over 20 years of experience in industry, research and academia. He joined as an Assistant Professor in the Department of Mechanical Engineering in Dec 2003. He has published over 330 articles in the peer-reviewed international journals and has delivered over 100 lectures in the international conferences. He has 4000+ citations for his publications & his h-index of 33, which endorses his high research productivity. Five of his patents are commercialized, total number of patents in his name being 88. He has procured a funding of over US $ 5 million so far at IIT Kanpur. Currently, he's the Project Investigator of MedTech facility, Imagineering Laboratory and RuTAG facility at IIT Kanpur. He is reviewer of 27 technical journals from Elsevier, Blackwell Publishing Inc., Wiley, Springer, Hindawi, Highwire, MRS India/ INSA, ACS Publications, Institution of Civil Engineers and American Society of Metals.
(E-mail: jrkumar@iitk.ac.in)