

Defect Detection in Welding using Thermal Image and semantic segmentation

Submitted in fulfillment of the requirements for the award of
Bachelor of Engineering degree in Mechatronics

by

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**DEPARTMENT OF MECHATRONICS
SCHOOL OF MECHANICAL ENGINEERING**

SATHYABAMA

**INSTITUTE OF SCIENCE AND TECHNOLOGY
(DEEMED TO BE UNIVERSITY)**

**Accredited with Grade "A" by NACC | 12B Status by UGC | Approved by AICTE
JEPPIAAR NAGAR, RAJIV GANDHI SALAI, CHENNAI - 600119**

MAY- 2023



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BONAFIDE CERTIFICATE

This is to certify that this Project Report is the bonafide work of **Srinivas P (39090053), Sudharshan N (39090055)** who carried out the project entitled "**Defect Detection in Welding using Thermal Image and semantic segmentation**" under our supervision from June 2022 to May 2023.

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We, **Srinivas P (39090053), Sudharshan N (39090055)**, hereby declare that the Project Report entitled “**Defect Detection in Welding using Thermal Image and semantic segmentation**” done by us under the guidance of **Mr. M. Amarnath, M.E.**, is submitted in fulfillment of the requirements for the award of Bachelor of Engineering degree in Mechatronics.

1.



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ABSTRACT

The large number of research studies on defect detection and classification using Deep Learning implies the demand for Artificial Intelligence in industrial automation systems. Welding is one of the crucial processes used in various industries with diverse applications, and one of the challenges faced in welding automation is the Defect identification using Non-Destructive Testing. The use of computer vision, X-ray images are some of the techniques that can be used to overcome these limitations., Using Defect detection algorithms and classification models, can be used to overcome the challenge of monitoring and automating the welding with high precision and consistency.

In this paper, we implement U-Net, a semantic segmentation model to detect various kinds of internal defects using thermal images. semantic segmentation using U-Net has the potential to significantly improve the efficiency and accuracy of welding defect detection. By automating the process, the time and resources required for inspection can be reduced, while the risk of human error is eliminated. As the technology continues to mature, it is likely that semantic segmentation using U-Net will become an essential tool for welding defect detection and analysis.

To automate that task we can count on machine learning to monitor the condition and adjust its parameters according to the input, and for that we need to have the best defect detection model to monitor it. We can use the defect detection model as a feedback provider in a closed loop system

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LIST OF ABBREVIATIONS

AI	Artificial Intelligence
ML	Machine Learning
CNN	Convolutional Neural Network
SOTA	State Of The Art
DL	Deep Learning
SVM	Support Vector Machine
MLP	Multi Layer Perceptron
MIG	Metal Inert Gas
TIG	Tungster Inert Gase
IR	INFRARED
LSTM	Long Short-Term Memory Network
RNN	Recurrent Neural Networks
GAN	Generative Adversarial Networks
GUI	Graphical User Interface
MSE	Mean Squared Error
MAE	Mean Absolute Error
RMSE	Root Mean Squared Error
IOU	Intersection Over Union

CHAPTER 1

INTRODUCTION

Welding is the technique of joining two or more pieces of metal or thermoplastics together. The building, manufacturing, automotive, and aerospace industries all employ welding. The welding processes MIG (Metal Inert Gas), TIG (Tungsten Inert Gas), stick welding, and flux-cored arc welding are just a few examples. Each procedure employs a unique set of tools and methods, but they all involve heating the metal surfaces to form a bond.

1.1 WELDING

For the creation of strong, long-lasting structures and products, welding is a necessary technique. In addition to being employed in the creation of automobiles, airplanes, and ships, it is also used in the construction of buildings, bridges, and highways. In addition, welding is essential for maintaining and repairing machinery and equipment.

1.1.1 Types of welding

TIG (Tungsten Inert Gas) Welding: A wire feed is used in MIG (Metal Inert Gas) welding to continuously supply the weld with filler metal. Steel, aluminum, and copper are just a few of the metals that this process can be applied to.

Stick Welding: A consumable electrode coated in flux is used in stick welding to form the weld. Although this strategy is straightforward and adaptable, it is less accurate than other options.

Flux-Cored Arc Welding: To produce the weld, flux is fed into the wire feed during flux-cored arc welding. This method is frequently applied in manufacturing and construction projects.

Submerged arc Welding: Submerged arc welding involves introducing a continuous wire electrode into a pool of molten metal that is covered in a flux layer.

This method is frequently used in commercial applications like pipeline construction and shipbuilding.

Gas welding: To heat the metal and form the weld, a flame created by burning a combination of gases is used in gas welding. Although this method is adaptable and can be applied to a variety of metals, it is slower and less accurate than other approaches.

The best welding technique for a given application depends on a number of variables, including the type of metal being welded, the thickness of the metal, and the desired result. Each type of welding has advantages and disadvantages of its own.

1.1.2 MIG (Metal Inert Gas) Welding

The welding we used is Metal Inert Gas. A Wire electrode and a shielding gas are used in the MIG (Metal Inert Gas) welding technique to fuse two or more pieces of metal together. As a result of its adaptability, simplicity, and high-quality outcomes, it is one of the most widely used welding techniques. The manufacturing, automotive, and construction industries, among others, all frequently use MIG welding.

1.1.3 Working

A wire electrode is fed into the weld junction using a welding gun in MIG welding. To shield the weld from contamination by ambient gases, the welding gun also discharges a shielding gas, such as argon or an argon-carbon dioxide mixture. A solid bond is created when the wire electrode melts and merges with the base metal.

The equipment needs to be set up properly before beginning the MIG welding process. This include choosing the proper wire type and size, the proper shielding gas, calibrating the welding machine's voltage and wire feed rate, and checking the welding gun and other tools for wear and tear. The operator holds the welding cannon, which is fed with a wire electrode. Wire is continuously fed into the weld junction from the cannon. A flux substance is applied to the wire electrode to assist shield the weld from impurities.

In order to shield the weld from atmospheric gases, a shielding gas is simultaneously released from the welding gun. Argon is the shielding gas most frequently used in MIG welding, but depending on the metal being welded, a mixture of argon and carbon dioxide may also be utilised. The wire electrode melts and fuses with the base metal as it is passed through the gun and into the weld joint. A strong, clean weld is ensured by the shielding gas, which shields the molten metal from ambient gases to prevent contamination.

By moving the welding gun along the joint's length, the operator keeps the arc's length and angle constant. The workpiece is held away from the welding gun so that the molten metal can flow into the junction uniformly. The workpiece must cool after the weld is finished before being relocated or receiving more attention. The metal solidifies and the weld gets stronger during the cooling process.

1.1.4 Advantages of MIG welding

Ease of use: MIG welding is a fairly straightforward method that is simple enough for beginners to master, and the equipment is simple to set up and use.

High productivity: MIG welding may be used to quickly join huge pieces of metal, making it perfect for high-volume production.

High-quality results: MIG welding creates strong, clear welds that need little post-welding cleanup or finishing.

Cost-effectiveness: Because of its high productivity and low post-welding cleanup, MIG welding is a cost-effective welding technique.

1.1.5 Disadvantages of MIG welding

Equipment costs:: The initial investment in MIG welding equipment can be rather significant, particularly if high-quality equipment is needed.

Limited to thin materials: MIG welding is only really effective on thin to medium-thick metals; it might not work on thicker materials.

Shielding gas required: MIG welding calls for the use of a shielding gas, which might raise the cost of the procedure.

Wind sensitivity: The shielding gas in MIG welding can be disturbed by wind or air currents, which leads to poor weld quality.

Safety risks: If sufficient safety precautions are not taken, MIG welding can present a safety risk to the operator by producing tremendous heat and brilliant light.

Welding calls for a high level of competence and skill because the procedure can be hazardous and necessitates the right safety measures to prevent injury. Welding highly relies on skilled manual welders. Another difficulty is the time required to carry it out. Let's see the overview of Computer Vision, Machine Vision, Deep Learning techniques that already exist in defect detection and identification.

1.2 TRADITIONAL APPROACHES

There have been many traditional approaches like determining weld penetration using ultrasonic sensors, Monitoring Joint Penetration Using IR Sensing , Multi-layer Perceptron , Machine Vision, which we will be looking at briefly.

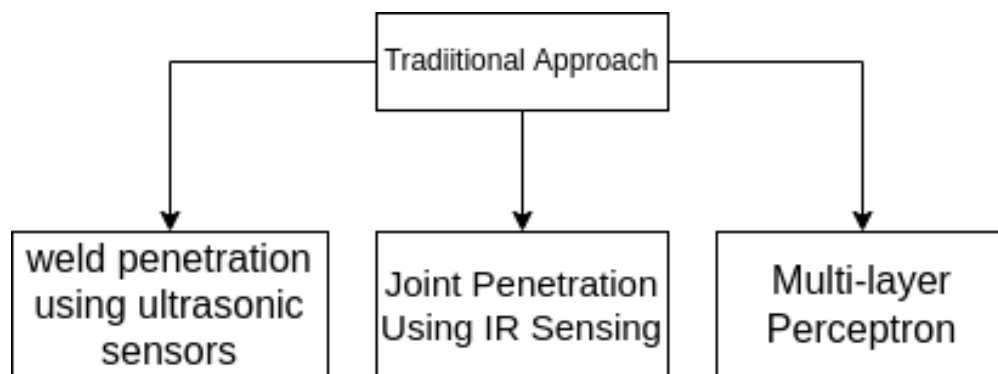


Fig:1.1: Classification of Traditional Approach

1.2.1 Determining Weld Penetration using Ultrasonic Sensor

In order to measure the quality and integrity of the weld, penetration is the main factor we need to look at. It's done here by using ultrasonic pulse echo techniques. There has also been a method where photodetectors were placed to measure the back bead width of the weld. When the weld transitions to full penetration, the IR radiation from the back side of the weld passes through a step transition, which can be detected by photodetectors. One of the drawbacks of it is that it is difficult to locate a sensor on the back side of the weldment for many weldment

configurations. To overcome this, Ultrasonic Testing is used. Ultrasonic testing has been used effectively as a NDE to detect lack of fusion, cracks and porosity. It's the process of transmitting ultrasonic pulse-waves into materials to detect internal flaws or to characterize materials.

If the length of the wave transmitted is less than the dimension of the material, the ultrasound pulse will rearrange the phase relationship of the incident pulse and there will be some change in the ultrasound pulse which is projected and the reflected one. From that we can extract the size and shape of it.

This method is suitable for detecting porosity and lack of penetration, But the difficulties in it is that there are difficulties in recording the reflected pulses if the material is thin. The following diagram shows the typical setup of detecting defects using an Ultrasonic sensor.

1.2.2 Monitoring Joint Penetration Using IR Sensor

First, an IR camera is set to monitor the surface temperature and molten pool during welding. A linear relationship exists between the infrared thermal image profile width and the bead width. There is also an exponential relationship between the depth and integrated area under the peak temperature profile.

1.2.3 Multi-layer Perceptron

Multi Layer Perceptron is a fully connected dense layer which transforms the dimension of input data to the desired data. The neurons in the Multi-layer perceptron are trained with the back propagation. Multilayer Perceptrons are designed to approximate continuous function.

The basic architecture of MLP consists of one input layer which receives the input, a hidden layer and an output layer which is based on the type of problem. In a single perceptron, linear problems can be solved, but it is not well suited for non-linear cases.

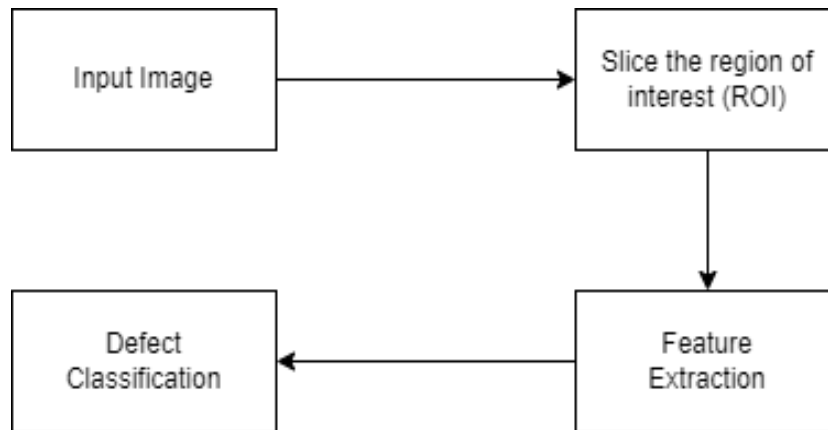


Fig:1.2: Flowchart of Multi Layer Perceptron

To solve these complex problems, Multi-layer perceptrons can be used . The weights of the network are initialized to random value. After completing the learning step by using the training data, the model is validated. Based on the result of validation, the optimization in Multi-layer Perceptron weights is done using the backpropagation algorithm, which attempts to minimize the error and improve the accuracy for further prediction.

1.3 WELD DEFECTS

Below are some of the commonly found weld defects listed.

1.3.1 Porosity

Porosity is a type of welding defect that occurs when gas pockets or voids are trapped within the welded material. The weld joint may become weaker and more prone to cracking or other sorts of failure due to porosity. Many things, such as poor shielding gas coverage, tainted filler, poor welding technique, or a lot of moisture in the welding environment, can result in porosity. Porosity can be avoided by keeping the welding area dry and free of moisture and other impurities, maintaining the welding equipment, and using the right welding procedure for the material being welded. Moreover, suitable filler materials and adequate shielding gas coverage should be used. A weld may need to be fixed if porosity is found in it, or the afflicted area may need to be taken out and rewelded. If the porosity has

little or no impact on the strength or integrity of the weld joint, it might be acceptable in specific circumstances.

1.3.2 Incomplete fusion

Incomplete fusion is a type of welding defect that occurs when the weld bead does not fully fuse with the base material, resulting in a weak joint. This can occur when the welding operation is carried out with insufficient heat or pressure or at an excessively rapid rate. When the margins of the connection are improperly prepared, such as when there is an excessive space between the two pieces of material being welded together, incomplete fusion can also happen. The weld bead may not be able to properly penetrate and fuse with the underlying material if sufficient preparation was not done.

It is crucial to correctly set up the joint and apply the right welding parameters, such as heat, pressure, and speed, to prevent partial fusion. The welder should also practise good technique, which includes maintaining a steady travel speed and a safe working distance. A weld may need to be repaired if there is evidence of incomplete fusion, or the damaged area may need to be taken out and rewelded. If the flaw does not impair the strength or integrity of the weld connection significantly, it might be acceptable in specific circumstances. To avoid the defect from recurring in the future, it is crucial to address its underlying cause.

1.3.3 Cracks

In welded constructions, cracks are a typical sort of welding failure that can happen. Many reasons, including excessive heat input, quick cooling, or high amounts of residual stress in the welded material, might cause cracks. The strength and integrity of the welded joint might be greatly reduced by cracks, which also raises the possibility of a catastrophic failure. In welded constructions, a variety of crack types, such as longitudinal, transverse, and crater cracks, can develop. Longitudinal cracks are parallel to the direction of the weld and might result from poor welding technique, insufficient fusion, or significant residual stress.

Transverse cracks can result from poor weld preparation, an excessively large weld bead, or high levels of stress. They run perpendicular to the direction of the weld. Crater fractures can be brought on by insufficient filler metal, poor welding technique, or thermal stresses. They appear at the end of a weld bead. Using the proper welding method and making sure the welding parameters are adjusted correctly for the particular material being welded are crucial for preventing cracks. In order to prevent overheating or rapid cooling during the welding process, the joint must be adequately prepared. In addition to reducing residual stress and preventing cracking, proper post-weld heat treatment can also be beneficial.

1.3.4 Undercutting

When the base metal close to the weld joint melts and is not fully filled in by the weld metal, undercutting is a form of welding problem that develops. As a result, the edge of the weld joint develops a groove or depression, which may weaken the joint and raise the possibility of failure. Several things, including improper welding technique, high welding current or voltage, or the wrong electrode angle, can result in undercutting. Moreover, it may happen if the welder moves too quickly or fails to keep the proper arc length.

Use the proper welding method, and make sure the welding parameters are set correctly for the particular material being welded, to avoid undercutting. In order to prevent overheating or rapid cooling during the welding process, the joint must be adequately prepared. To make sure that the weld metal fills the groove entirely, the electrode angle should be maintained continuously and the welding speed should be adjusted as needed.

1.3.5 Burn through

Burn through is a type of welding defect that occurs when the weld metal melts through the base metal, resulting in a hole or penetration. Burn through can make the joint less strong and less intact.

A number of things, including high welding current or voltage, poor welding technique, or employing the wrong kind of electrode, can result in burn through.

Moreover, it may happen if the welder moves too slowly or fails to keep the proper arc length.

Use the proper welding procedure, and make sure the welding parameters are set appropriately for the particular material being welded, to prevent burn through. In order to prevent overheating or rapid cooling during the welding process, the joint must be adequately prepared. To prevent the weld metal from melting through the base metal, the welding speed should be adjusted as appropriate.

If burn through is found, the weld's damaged area may need to be fixed or changed entirely. To make sure that the hole is completely filled and the welded union is strong, this may entail removing the present weld and beginning afresh or doing additional passes over the area

1.3.6 Inclusions

Inclusions are a type of welding defect that occur when non-metallic materials, such as slag or oxide particles, are trapped in the weld metal. Inclusions can weaken the welded joint, lower its strength, and compromise its integrity, increasing the likelihood that it will fail.

A number of things, including poor welding technique, insufficient joint preparation, and subpar welding materials, can result in inclusions. They may also be brought on by inadequate shielding gas or poor gas flow while welding.

Use the proper welding technique, and make sure the welding parameters are set correctly for the particular material being welded, to prevent inclusions. To prevent contaminating the weld metal, the junction must be properly prepared and the welding process must be closely monitored. Throughout the welding operation, proper shielding gas and gas flow should be maintained.

If inclusions are found, the weld's damaged area could need to be fixed or replaced. To make sure that the non-metallic materials are eliminated and the welded joint is strong, this may entail removing the present weld and beginning afresh or making further passes over the area.

1.3.7 Spatter

Spatter is a type of welding defect that occurs when small droplets of molten metal are ejected from the welding arc and land on the surface of the welded joint or surrounding areas. Spatter can harm neighbouring parts or equipment in addition to causing a rough, uneven surface on the welded junction. Spatter can be brought on by a number of things, including poor welding technique, the use of the incorrect electrode, and poor welding settings. It may also be brought on by subpar welding supplies or insufficient shielding gas.

Use the proper welding method, and make sure the welding parameters are set correctly for the particular material being welded, to avoid spatter. The welding process should be carefully managed to prevent excessive heat input or quick cooling, and the electrode should be chosen based on the material being welded and the desired weld qualities. Proper shielding gas and gas flow should be maintained throughout the welding process. If spatter is found, the damaged areas should be cleaned, and the splatter's cause should be found and fixed. Wire brushes and grinding tools can be used to remove the spatter, but caution should be exercised to prevent damage to the welded connection or neighbouring components.

Frequent testing and inspections can aid in the early detection of spatter and other welding flaws, enabling quick correction and guaranteeing that the finished product satisfies the necessary standards for strength and safety.

1.3.8 Concavity

Concavity is a type of welding defect that occurs when the weld metal does not fill the joint completely, resulting in a depression or concave surface. This may weaken the welded connection, lessen its strength, and compromise its integrity, increasing the likelihood of failure. Several things, including poor joint preparation, insufficient welding technique, and incorrect welding parameters, can result in concavity. Incorrect electrode angle or insufficient welding current can also be the reason.

Using the proper welding method and making sure the welding parameters are adjusted correctly for the particular material being welded are crucial for preventing concavity. To ensure that the weld metal fills the connection entirely, the joint must be properly prepared and the welding process must be closely monitored. If concavity is found, the weld's affected area could need to be fixed or replaced. To make sure that the connection is completely filled and the welded junction is strong, this may entail removing the present weld and beginning afresh or performing extra passes over the area.

1.3.9 Misalignment

Misalignment is a type of welding defect that occurs when the welded joint is not properly aligned, resulting in an uneven or distorted joint. This may weaken the welded connection, lessen its strength, and compromise its integrity, increasing the likelihood of failure. A number of things, including inadequate joint preparation, bad clamping or fixturing, or poor welding technique, can result in misalignment. It can also be brought on by employing the incorrect welding method or electrode for the intended use.

Before to welding, it is crucial to make sure that the joint is correctly prepared and aligned to prevent misalignment. The components should be securely held in position during the welding process by the clamping or fixturing. To guarantee that the welded junction is correctly aligned and that the weld metal is deposited uniformly, the welding process should be carefully managed. If misalignment is found, it might be necessary to replace or repair the weld in question. To make sure that the joint is correctly aligned and the welded joint is strong, this may entail removing the present weld and beginning afresh or performing additional passes over the area.

1.3.10 Lack of penetration

A weak and shallow weld results from a welding problem known as lack of penetration, which happens when the weld metal does not sufficiently penetrate into the base metal. This may weaken the welded connection, lessen its strength, and compromise its integrity, increasing the likelihood of failure. A number of things, including employing the incorrect welding parameters, using the electrode

at the inappropriate angle or distance, or not properly preparing the joint, might result in a lack of penetration. Insufficient shielding gas or subpar welding supplies may also be at blame.

Use the proper welding technique, and make sure the welding parameters are set correctly for the particular material being welded, to prevent lack of penetration. To make sure that the weld metal penetrates completely into the base metal, the electrode angle and distance should be constantly maintained, and the welding speed should be adjusted as needed. Throughout the welding operation, proper shielding gas and gas flow should be maintained. If there is no penetration, the weld may need to be repaired or replaced in the affected area. In order to make sure that the weld metal penetrates completely into the base metal, this may need removing the previous weld and beginning afresh, or it may involve making several passes over the area.

1.4 INTRODUCTION TO COMPUTER VISION USING AI

Artificial Intelligence has been used widely in many sectors from manufacturing, production, fault diagnosis and condition monitoring. They outperform traditional approaches in automation and in many industries

1.4.1 Artificial Intelligence

Rapid advances in the field of artificial intelligence revolutionized many fields such as computer vision, Natural Language processing and Recommender System. Recently, AI is solving complex problems in various domains consistently with high precision. AI can mimic human intelligence up to certain limits with certain limitations, at this point AI started to get its attention in 1989 from automatic digit recognition [8] by using convolutional neural network (CNN). Convolutional neural network (CNN) are better at extracting features from images than the other approaches.

AI is the overarching umbrella encompassing computer vision, Natural Language Processing, Reasoning, machine learning, Deep Learning, etc. Machine learning (ML) is a subset of Artificial Intelligence (AI) that allows one to make a prediction with high accuracy without explicitly programming.

1.4.2 Classification of Machine Learning:

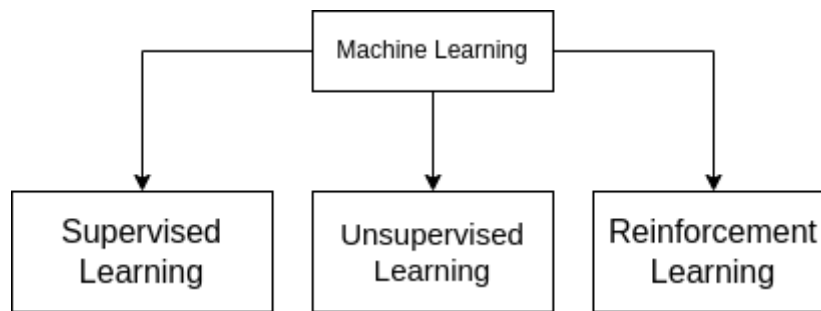


Fig:1.3: Classification of Machine Learning

1.4.3 Supervised Learning

Supervised machine learning creates a function for prediction based on labelled data. The training data consist of features whose characteristics are known. The correct label of the training data is given. The training data is passed to the algorithm, and it optimizes itself and creates a function which has minimum loss. The algorithm should be able to generalize the training data in such a way that it can predict the even unseen data.

1.4.4 Unsupervised Learning

Unsupervised machine learning is the formulation of a function based on unlabeled data. The algorithm scans through the entire data to discover hidden patterns or data groupings without any intervention. Dimensionality and clustering algorithms come under this type.

1.4.5 Reinforcement Learning

Reinforcement learning is an area of Machine Learning which has grown enormously in the past couple of decades. It is about taking suitable action to maximize reward in a given situation. The agent will be able to find the best possible behavior or path it should take in a specific state. The agent will be able to optimize itself based on the reward it receives for the action it took.

1.5 DEEP LEARNING

Deep Learning using convolutional neural networks has been overwhelmingly successful in computer vision, and is the most common technique in detecting objects. Unlike the traditional computer vision techniques, In this paper, our focus is on computer vision. We provide a systematic review of recent achievements, technique that can be incorporated into our application. In the early stage of computer vision development, deep learning was not preferred as it's computationally expensive. So the computer vision researchers were only incorporating machine learning techniques such as Support Vector Machine, K-Nearest Neighbor, Random Forest, etc.

In the past two decades there has been enormous amount of development in deep learning because of the improvement in computation power which led to the development of many architectures such Convolutional Neural Networks (CNNs), Long Short-Term Memory Networks (LSTMs), Recurrent Neural Networks (RNNs), Generative Adversarial Networks (GANs), etc.

Since the outstanding performance in the ImageNet competition, Convolutional Neural Networks have become the go-to DL approaches. Few of the applications of Computer Vision are object detection and object classification. The main advantage of the CNN is that it requires no feature extraction and calculation compared to traditional approaches. The CNN consists of convolutional layers, pooling layers, and fully connected layers. In the convolutional layers, a CNN uses various kernels to convolve the whole image and extract the useful features .

The prediction accuracy of deep learning models can be improved by having large model sizes. Deeper and wider network architectures such as InceptionV1 and VGG-Net gave classification performances across applications.

1.5.1 Convolutional Neural Network

Instead of preprocessing the image to extract features from an image, we can pass the raw image to CNN to learn and extract the features on its own. First a

3-D image is passed as input where each dimension represents each primary colour (RGB) and the input layer is followed by a bunch of blocks which perform element wise dot product between a subarray of an input array and a receptive field (Kernel). Each kernel has its own weight which is updated for each iteration and then the multiplied values are summed, and bias is added to it. This results in a convolved feature matrix.

During training, the CNN's kernel matrices optimizes its value to extract meaningful features.

One of the advantages of the convolution is that it reduces the shape of the input image, which in turn reduces computational cost. A hyperparameter called stride plays an important role in it. The stride defines how many of the receptive field's columns and rows slide at a time across the input array's width and height. Stride size is inversely proportional to the output size. In order to introduce nonlinearity into the model, an activation function is applied. There are many types of activation functions.

After convolution the pooling step is carried out, where the CNN downsamples the convolved feature, reducing the number of dimensions without losing any feature information. A common pooling method used for this process is called max pooling. There are other pooling techniques like mean, average, spatial, etc.

The fully connected layer is introduced after the convolutional blocks. The output of this mentioned network is a one-dimensional vector as a probability function with the total number of elements to be classified. It indicates how well the input images are trained and predicted for each type of class.

1.6 TRANSFER LEARNING FOR DEFECT DETECTION

As the first layers of CNN kernels act as Color blob detectors and filters which seems to be very general, we can utilize a network to recognize image/object categories it never trained on. Models trained on one dataset can transfer the features to another. Generally, two forms of transfer learning exist in deep learning for computer vision:

- Use Pre-existing State of the art (SOTA) model and training it completely with our own dataset
- Replacing the fully connected layers of the pre-trained Neural Network model with the Fully Connected layer of our choice.

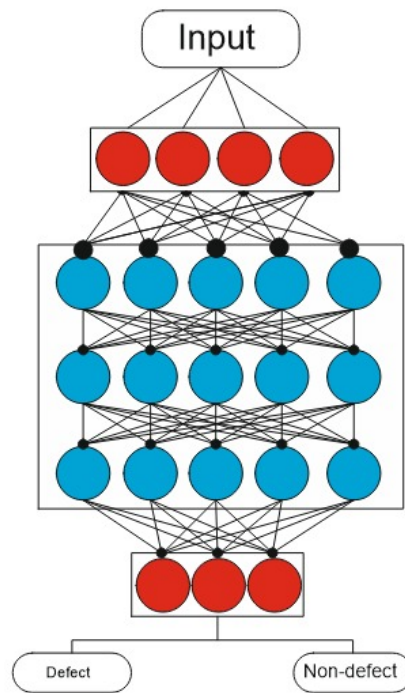


Fig:1.4: Architecture of Neural Network

CHAPTER 2

LITERATURE SURVEY

The following are the literature survey that has been done on the applications of Non-destructive testing and Computer Vision on weld defect detection

A.A. Carvalho, J.M.A. Rebello, M.P.V. Souza, L.V.S. Sagrilo, S.D. Soares, Reliability of non-destructive test techniques in the inspection of pipelines used in the oil industry, *International Journal of Pressure Vessels and Piping*, Volume 85, Issue 11, November 2008, Pages 745–751: A.A. Carvalho, *Et al* aims to evaluate the reliability of NDT techniques used to inspect of pipeline welds in the petroleum industry. It used radiography as well as manual and automatic ultrasonic techniques using pulse-echo and time of flight diffraction. Analysis of three classes of defects was performed: lack of penetration, lack of fusion and undercut. The specimen was made from pipelines containing defects, which had been artificially inserted on laying the weld bead. These specimens were subject to tests. The results of this work show that automatic ultrasonic technique is superior for the detection of defects in pipelines in comparison with the manual ultrasonic and radiography. Automated techniques showed higher probability of detection in all situations and sizing errors were smaller for internal defects. Besides, automated tests reduced the time of inspection.

Akapot Tantrapiwat - Spot Welding Defect Detection Using Synthetic Image Dataset on Convolutional Neural Networks: In this paper Convolutional neural networks (ConvNet) was used to detect welding defects this technique requires a large number of input images in order to train the network. This is not practical as the defective workpieces are undesirable and often rare. This study proposes the use of synthetic images which imitate the defective spot-welding characteristic as the input dataset. By replicating Heat Effected Zone Ring, Fusion Zone Ring ,and Melt Ring in different size, color, and shape, both abnormal and typical spot welding images can be generated using image processing program. These images were then used to train two different levels of classification ConvNet. The results

showed that by using two thousand artificial images, the ConvNet can classify the defective spot welding at the accuracy above 98%. Finally a test set of real defective spot welding images were carried out. The outcome also yielded the similar performance.

A. Masnata and M. Sunseri, Neural network classification of flaws detected by ultrasonic means, *NDT & E International*, Volume 29, Issue 2, April 1996, Pages 87-93: A. Masnata, *Et al* proposed a methodology for the automatic recognition of weld defects, detected by a P-scan ultrasonic system, which has been developed within two stages in the present work. In the first stage, Fischer linear discriminant analysis is used to perform a selection of the shape parameters defining the pulse-echo envelope reflected from a generic flaw, and defined in the time domain. In the second stage, the input values are the parameters selected by the Fischer analysis and the classification is carried out by a three-layered neural network trained with the backpropagation rule.

C'Shekhar N Shitole, O Zahran and W Al-Nuaimy , Combining fuzzy logic and neural networks in classification of weld defects using ultrasonic time-of-flight diffraction, *Insight - Non-Destructive Testing and Condition Monitoring*, Volume 49, Number 2, 1 February 2007, pp. 79-82(4): C'Shekhar N Shitole, *Et al* have used advanced methods for automatic interpretation and classification of weld defects in Time Of Flight Diffraction (TOFD) data. A comparison of three different classification techniques namely: an artificial neural network-based classifier, a fuzzy logic-based classifier and a hybrid neural-fuzzy classifier is performed in the classification stage. A neural classifier learns from data, but the output does not lend itself naturally to interpretation. A fuzzy classifier cannot learn, but consists of interpretable linguistic rules. A neural fuzzy classifier combines the merits of both neural and fuzzy classifiers while overcoming their drawbacks and limitations. It is based on a three-layer feed-forward neural network. The TOFD technique affords a fully automated inspection system for detection, interpretation and classification of weld defects. The developed neural-fuzzy classifier shows great potential and

exhibits high levels of accuracy, consistency and reliability, with low times for computation. The fuzzy-neural based classifier combines the benefits of both neural networks and fuzzy logic and provides better performance, paving the way for a new paradigm in ultrasonic for automatic defect classification systems.

Daniel Bacioiua , Geoff Melton , Mayorkinos Papaeliasa , Rob Shaw- Automated defect classification of Aluminium 5083 TIG welding using HDR camera and neural networks; Journal of Manufacturing Processes volume 45, September 2019, Pages 603-613: The system described in this paper uses an HDR camera and artificial neural networks (ANN) for image processing to evaluate tungsten inert gas (TIG) welding. This paper proposes a new dataset 1 comprising photos of the TIG welding process in the visible spectrum with better contrast, similar to what a welder would typically view. Additionally, a methodology for calculating a label indicating the welding flaw is proposed. Weldment classification is done using a vision system composed of an HDR camera able to offset powerful arc light and capture more detailed imaging of the weld pool, paired with the new and adaptive classification paradigm of neural networks. The models were trained using 6-class, 4-class, and 2-class tests with the highest accuracies of 71%, 89%, and 95%, respectively.

DE Hardt, JM Katz - Ultrasonic measurement of weld penetration; Welding Journal: This research examines a method for measuring the size of weld pools using ultrasonic pulse-echo measurements. Since penetration is a reliable first-order indicator of weld integrity, penetration has been the focus of most efforts to control the quality of welds. This work advances the idea of measuring the size of a weld pool while it is being formed using reflection ultrasound technologies. Although methods for direct shape measuring by decoding the full ultrasonic reflection are being developed, simpler methods must first be taken into account due to the extra issues raised by welding's high temperatures and significant temperature differential. This study predicts and experimentally validates the reflection pattern from hemispheres at the ends of long cylinders.

J. Mirapeix, P.B. Garcí'a-Allende, A. Cobo, O.M. Conde, J.M. Lopez-Higuera, Real-time arc-welding defect detection and classification with principal component analysis and artificial neural networks, *NDT & E International*, Volume 40, Issue 4, June 2007, Pages 315–323: J. Mirapeix, *Et al* developed a new method that combines principal component analysis and an artificial neural network to automatically detect and classify weld defects. PCA is used to process the plasma spectra that were recorded during the welding process. Through the use of spectral data compression, processing complexity is decreased. The developed ANN enables for the automatic detection of weld flaws following the selection of the appropriate data training set.

Junyi Chai. Hao Zeng. Anming Li. Eric W.T.Ngai - Deep learning in computer vision: A critical review of emerging techniques and application scenarios: This paper reviews on computer vision. It provides a critical review of recent achievements in terms of techniques and applications. It speaks about the eight emerging techniques : (1) AlexNet, (2) VGGNet, (3) GoogLeNet & Inception, (4) ResNet, (5) DenseNet, (6) MobileNets, (7) EfficientNet, and (8) ResNet also investigates their origins, and updates, and finally emphasizes their applications, including recognition, visual tracking, semantic segmentation, and image restoration. Explains the three development stages in the past decade and emphasize research trends for future works.

Neury Boaretto, Tania Mezzadri Centeno Automated detection of welding defects in pipelines from radiographic images DWDI; *NDT & E International*: This paper presents a method for the automatic detection and classification of defects in radiographic images of welded joints obtained by exposure technique of double wall double image (DWDI). The proposed method locates the weld bead on the DWDI radiographic images, segments discontinuities (potential defects) in the detected weld bead, and extracts features of these discontinuities. These features are used in a feedforward multilayer perceptron (MLP) with backpropagation learning algorithm to classify discontinuities in “defect and no-defect”. The

classifier reached an accuracy of 88.6% and a F-score of 87.5% for the test data. A comparison of the results with the earlier studies using SWSI and DWSI radiographic images indicates that the proposed method is promising.

Ravi Sekhar , Deepak Sharma and Pritesh Shah -Intelligent Classification of Tungsten Inert Gas Welding Defects: A Transfer Learning Approach: This paper presents a transfer learning approach for accurate classification of tungsten inert gas (TIG) welding defects while joining stainless steel parts. In this approach, eight pre-trained deep learning models were explored to classify welding images into two-class (good weld/bad weld) and multi-class (good weld/burn through/contamination/lack of fusion/lack of shielding gas/high travel speed) classifications. Moreover, four optimizers were applied separately to each of the deep learning models to maximize prediction accuracies. All models were evaluated based on testing accuracy, precision, recall, F1 scores, training/validation losses, and accuracies over successive training epochs. Primary results show that the VGG19-SGD and DenseNet169-SGD architectures attained the best testing accuracies for two-class 99.69% and multi-class 97.28% defects classifications, respectively. For “burn through,” “contamination,” and “high travel speed” defects, most deep learning models ensured productivity over quality assurance of TIG welded joints.

Samuel Kumaresan, K. S. Jai Aultrin, S. S. Kumar ,M. Dev Anand - Transfer Learning With CNN for Classification of Weld Defect: This paper uses DNN produces considerably good results in fields which offer big dataset for it to train. DNN trained with small datasets by conventional methods produces less accurate results. This limits the use of DNN in many fields. This study focuses to overcome this limitation, by adopting transfer learning using Pre-trained deep convolutional neural networks. By this method, a weld defect radiographic image classifier, which can classify 14 types of weld defects, was constructed. 940 Image patches of weld defects were manually collected and labelled from GDXray database. Subsequently the features of this weld defect dataset were extracted using VGG16

and ResNet50 CNNs, both pre-trained on the ImageNet database. Then machine learning models such as Logistic Regression, Support Vector Machine (SVM) and Random Forest were trained on these extracted features. The Classifier based on SVM trained on features extracted by ResNet50 outperforms the other counterparts with an accuracy of 98%. In all these cases, transfer learning improves performance and reduces the training time and computational system requirements.

W. CHEN AND B. A. CHIN - Monitoring Joint Penetration Using Infrared Sensing Techniques; WELDING RESEARCH SUPPLEMENT: The objective of this research paper is to apply infrared sensing and computer image processing techniques to improve the welding process through dynamic control of joint penetration parameters. A front-side scanning infrared camera was used to monitor the molten pool and surface temperature distributions surrounding the pool during the welding process. Welding parameters were varied to change the depth of penetration and the corresponding changes in the temperature distributions recorded. A linear relationship exists between the width taken at the mid-temperature of the peak temperature profile during the welding process and the bead width. This paper suggests that Infrared thermographic may be applicable to adaptive control of joint penetration and bead width during GMA welding of steel, and an exponential relationship exists between the depth of joint penetration and integrated area under the peak temperature profile obtained during the welding process.

William Lucas, Dan Bertaso, Geoff Melton, Jeremy Smith & Chris Balfour - Real-time vision-based control of weld pool size: In this paper, a computer vision technique based on the real-time measurement and control of the upper surface or 'topface' weld pool size is discussed. The primary objective is to demonstrate the feasibility of using vision-based image processing to provide measurements and subsequent control of a weld's geometrical properties during the weld formation or molten phase. A novel reference feature a correlation-based image analysis

algorithm has been developed, which may be configured to operate with a number of different welding processes.

Young-Jin Cha* & Wooram Choi - Deep Learning-Based Crack Damage Detection Using Convolutional Neural Networks: This article proposes a vision-based method using a deep architecture of convolutional neural networks (CNNs) for detecting concrete cracks without calculating the defect features. As CNNs are capable of learning image features automatically, the proposed method works without the conjugation of IPTs for extracting features. The designed CNN is trained on 40 K images of 256×256 -pixel resolutions and, consequently, records with about 98% accuracy. The trained CNN is combined with a sliding window technique to scan any image size larger than 256×256 -pixel resolutions. The robustness and adaptability of the proposed approach are tested on 55 images of $5,888 \times 3,584$ -pixel resolutions taken from a different structure which is not used for training and validation processes under various conditions (e.g., strong light spots, shadows, and very thin cracks).

Y. LeCun, B.E. Boser, J.E. Denker, D. Henderson, R.E. Howard, W.E. Hubbard, and L.D. Jackel. Handwritten digit recognition with a back-propagation network. In D. S. Touretzky, editor, *Advances in Neural Information Processing Systems 2*, pages 396– 404. Morgan-Kaufmann, 1990: This paper uses the application of back-propagation networks to handwritten digit recognition. Minimal pre-processing of the data was required, but the architecture of the network was highly constrained and specifically designed for the task. The input of the network consists of normalized images of isolated digits. The method had a 1 % error rate and about a 9% reject rate on zip code digits provided by the U.S. Postal Service. The network architecture and the constraints on the weights were designed to incorporate geometric knowledge about the task into the system. Because of its architecture, the network could be trained on a low-level representation of data that had minimal pre-processing. Because of the redundant nature of the data and because of the constraints imposed on the network, the learning time was

relatively short considering the size of the training set. Scaling properties were far better than one would expect just from extrapolating results of back-propagation on smaller, artificial problems.

A Machine Vision-Based Method for Detecting Surface Hollow Defect of Hot-State Shaft in Cross Wedge Rolling - Huajie Fu , Ying Wang, Xuedao Shu , Xiaojie Chen and Kai Li : This paper proposes an intelligent classification approach for tungsten inert gas (TIG) welding defects using transfer learning. The proposed method utilizes a convolutional neural network (CNN) architecture to extract features from the welding images, which are then fed to a support vector machine (SVM) classifier for defect classification. The authors employ transfer learning to utilize pre-trained CNN models to extract the features, reducing the computational complexity of the training process. The proposed approach achieves high accuracy in defect classification, demonstrating the effectiveness of transfer learning in improving the performance of the CNN-SVM classification model. The paper presents experimental results to validate the proposed approach's performance, showing its superiority over traditional machine learning methods. The authors conclude that transfer learning can significantly improve the accuracy and efficiency of welding defect classification and suggest further exploration of this approach in other welding defect classification problems.

Automatic Defects Segmentation and Identification by Deep Learning Algorithm with Pulsed Thermography: Synthetic and Experimental Data by Qiang Fang Clemente Ibarra-Castanedo and Xavier Maldague: The paper presents a deep learning algorithm for automatic defects segmentation and identification using pulsed thermography. The proposed method uses a convolutional neural network (CNN) architecture to extract features from the thermographic images and segment the defects automatically. The authors evaluate the proposed approach using both synthetic and experimental data and compare its performance with traditional machine learning methods. The experimental results show that the proposed approach achieves high accuracy in defect segmentation and identification, outperforming the traditional machine learning methods. The paper also discusses the limitations and challenges of the proposed method and suggests future research directions for improving the accuracy and efficiency of defect segmentation and identification using pulsed thermography.

Chen, L.C.; Zhu, Y.; Papandreou, G.; Schroff, F.; Adam, H. Encoder-decoder with atrous separable convolution for semantic image segmentation. In Proceedings of the European Conference on Computer Vision, Munich1., Germany, 8–14 September 2018;pp. 801–818: The paper proposes a novel encoder-decoder architecture for semantic image segmentation, which uses atrous separable convolutions to achieve high accuracy while maintaining low computational complexity. The proposed architecture consists of an encoder network that extracts high-level features from the input image and a decoder network that generates the segmentation map by upsampling the feature maps to the original image size. The encoder network uses an atrous separable convolutional block, which consists of a depthwise separable convolution followed by a dilated convolution, to extract multi-scale features from the input image. The decoder network uses an upsampling block to recover the spatial information lost during the downsampling process and combines the feature maps from different scales to generate the final segmentation map. The proposed approach achieves state-of-the-art performance on several benchmark datasets, including PASCAL VOC 2012 and Cityscapes. The authors demonstrate that the proposed architecture outperforms existing approaches in terms of accuracy and efficiency, with a significant reduction in the number of parameters and computation time. The paper also presents an ablation study to evaluate the contributions of each component in the proposed architecture, showing that the atrous separable convolutional block and the multi-scale feature fusion are critical for achieving high accuracy in semantic segmentation tasks. In conclusion, the proposed encoder-decoder architecture with atrous separable convolutions provides a promising approach for semantic image segmentation, achieving high accuracy while maintaining low computational complexity. The proposed architecture can be applied to a wide range of computer vision tasks, including object detection and image classification, and can significantly improve the performance of existing models.

Fu, G.; Sun, P.; Zhu, W.; Yang, J.; Cao, Y.; Yang, M.Y.; Cao, Y. A deep-learning-based approach for fast and robust steel surface defects classification. *Opt. Lasers Eng.* 2019, 121, 397–405: The paper proposes a deep learning-based approach for fast and robust steel surface defects classification.

The proposed method utilizes a deep convolutional neural network (CNN) architecture to automatically detect and classify steel surface defects in real-time. The authors use transfer learning to pre-train the CNN on a large dataset and fine-tune it on a small dataset of steel surface defect images, reducing the amount of training data required and improving the generalization performance of the model. The experimental results show that the proposed approach achieves high accuracy in steel surface defects classification, outperforming traditional machine learning methods. The proposed method is also computationally efficient, enabling real-time defect detection and classification. The authors compare the proposed method with existing approaches and demonstrate its superiority in terms of accuracy, efficiency, and robustness to various lighting conditions and surface textures. The paper discusses the potential applications of the proposed method in the steel industry, including quality control and automated inspection of steel surfaces. The proposed method can significantly improve the efficiency and accuracy of steel surface defect classification and reduce the labor costs associated with manual inspection. The authors suggest future research directions for further improving the performance of the proposed approach, such as incorporating additional sensor data and optimizing the CNN architecture.

CHAPTER 3

AIM AND SCOPE

3.1 AIM

To develop a Deep Learning model using State-of-the-art techniques to find the defects in welded material.

3.2 OBJECTIVES

- Identity and collect images of several types of defects in welded materials using thermal camera
- Annotate them and Augment them to generate more samples
- Train several types of models and select the one that performs better after hyperparameter tuning.
- Validate them against test dataset
- Create a GUI and make it as an interactive application

3.3 SCOPE OF THE INVESTIGATION

Industrial Robots allow welders to automate the welding process and help reduce the labor cost while also solve the complex problems. This also reduces many of the risks that welding professionals pose from very complex welds. Robots help perform quick, repeatable tasks, allowing welders to focus on detail-oriented tasks. This helps the industry to focus on the main problems faced by welders while leaving the monotonous tasks to robot

Research is also conducted to solve more complex problems that should be accident free. This scope of the study is to provide a complete end-to-end setup for defect detection in welding using thermal cameras. We use a thermal camera connected to Raspberry Pi to run our deep learning model and predict the defect either through segmentation approach or bounding box approach. Prevailing Defects in previously welded plates are annotated first and fed into the model.

This helps the researcher or welders to couple it with a closed loop control system as it provides feedback for the decision to take. The following figure illustrates the proposed model for control system that's coupled with AI model.

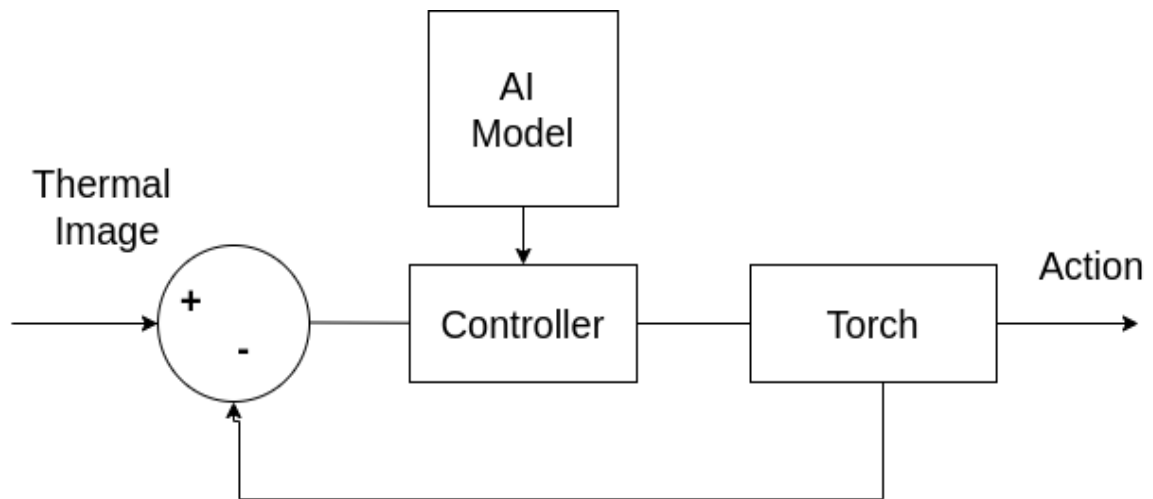


Fig:3.1: Example of Control System couple with AI

CHAPTER 4

EXPERIMENTAL METHODS AND ALGORITHM USED

4.1 METHODOLOGY

The End-to-End solution for this problem starts from connecting a Raspberry Pi to a thermal camera (FLIR LEPTON)and running a script to generate thermal images, then using augmentation techniques to generate several images to increase the size of the dataset and annotating them to train our Deep Learning Model.

After training our model, a GUI is used to upload images and then displays where the defect is present.

4.2 EXPERIMENTAL SETUP DETAILS

4.2.1 Hardware Setup

To capture the thermal image, FLIR LEPTON thermal camera is connected to Raspberry Pi and compiled. A compact thermal camera module called the FLIR Lepton 1.5 is created for integration into a variety of products.

It can take thermal photos and detect infrared radiation using a microbolometer sensor. The Lepton 1.5 has many characteristics that make it simple to integrate into various systems. It provides an I2C interface for interacting with various sensors in addition to a straightforward SPI interface that a microcontroller can manage.

The camera module is the perfect size for using in battery-powered gadgets because it uses very little power and is only 8.5mm x 11.7mm x 5.6mm in size.

The Raspberry Pi Foundation created a line of compact single-board computers known as Raspberry Pi. Since the initial Raspberry Pi was introduced in 2012, other versions of the gadget have been made available since then.

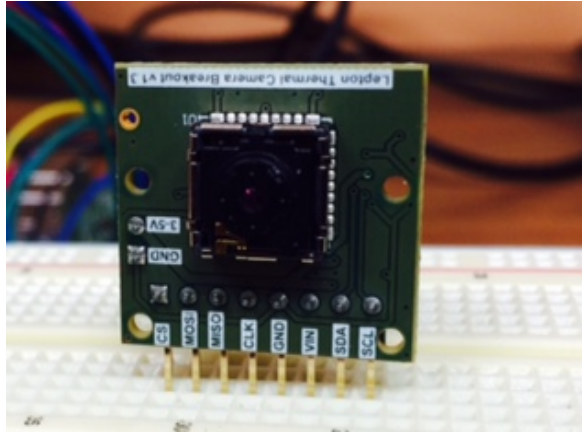


Fig:4.1: Flir Lepton Thermal Camera

4.2.2 Collecting Images using thermal camera

After Compiling the FLIR LEPTON thermal camera, the script to capture the image is executed to capture the thermal image. we can input the frame rates per second (how much frame the camera will capture per second) and the path to the directory where it will be stored as input to the command prompt and once we.

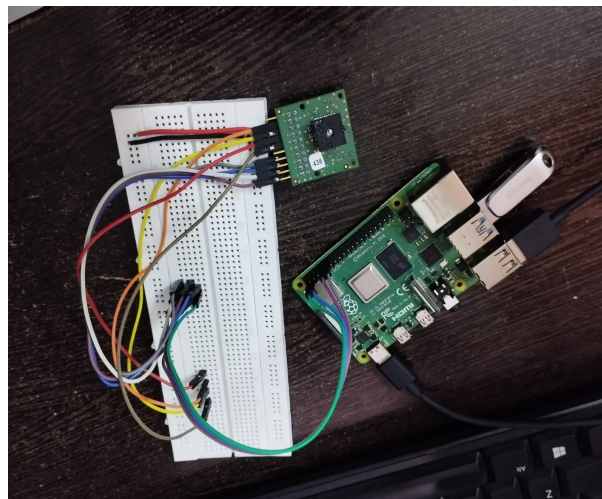


Fig:4.2: Raspberry Pi + Thermal Camera

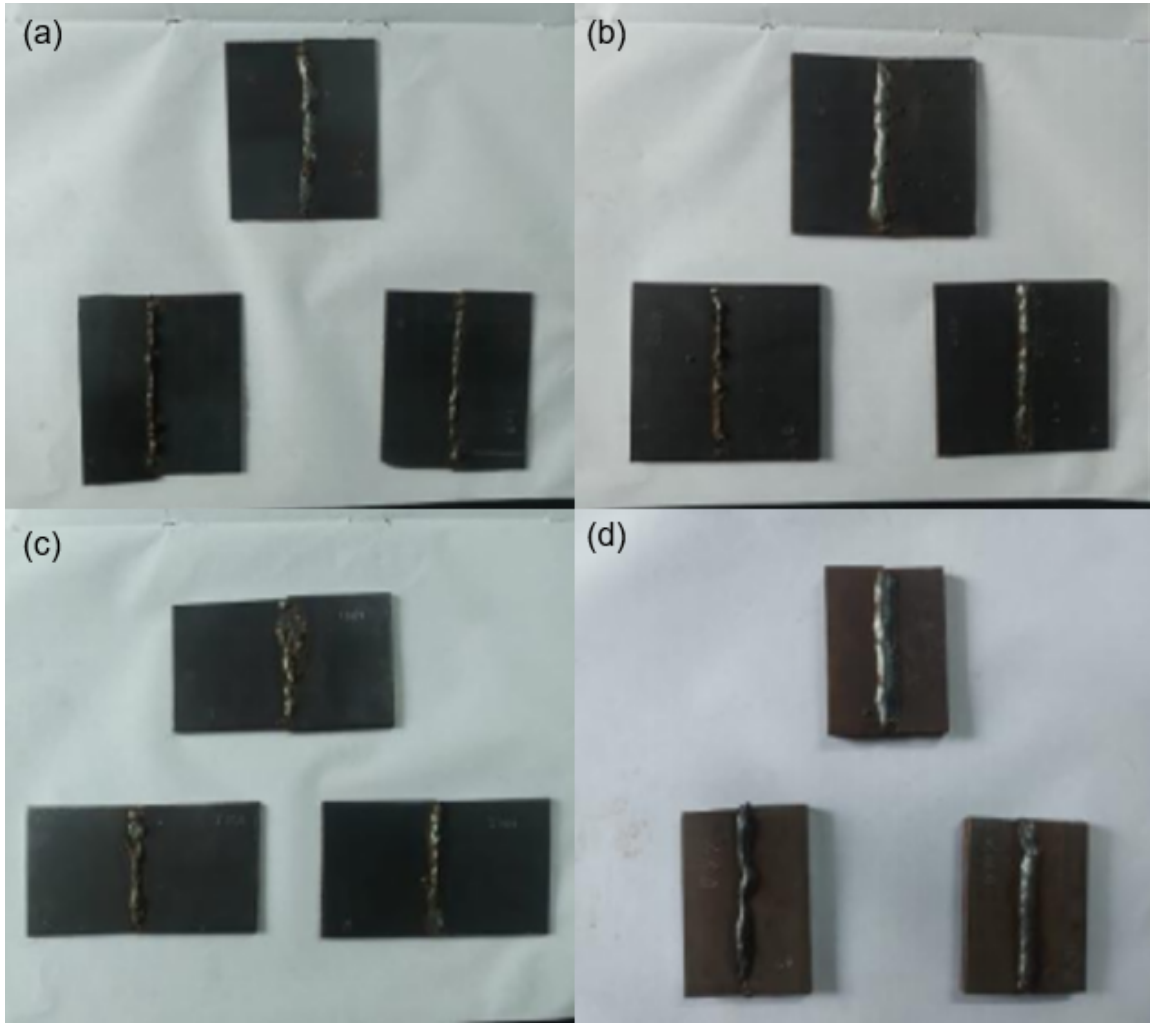


Fig: 4.3: Thickness samples - (a) 4MM , (b) 1.5MM ,(c) 3MM ,(d) 6MM

4.2.3 Annotating images

The annotating process involves annotating the data with meaningful tags or categories that correspond to the desired output of the model. There are many annotation tools available, such as Labelbox , VGG Image Annotator (VIA), Roboflow, labeling. The choice of us is label-studio which has wide features for object detection, object segmentation, etc. In Semantic segmentation each pixel in an image is labeled with a corresponding class label. The class labels can be differentiated using different colors. The defects we focused on are four (Misalignment, Excessive Reinforcement, Concavity, Spatter).

Label Studio is an open-source data labeling platform that simplifies and streamlines the labeling process for deep learning. It provides a user-friendly interface for creating labeling tasks, managing annotation projects, and collaborating with team members. Label Studio also offers a range of labeling tools, including text, image, and audio annotation, as well as support for custom labeling workflows and extensions.

4.2.4 Creating a GUI:

A Graphical User Interface is created to input the images or monitor the defect and show where the defect is in real time. We used PyQt5 to create the Graphical User Interface with options of uploading Videos as well as images.

OpenCV and Pillow Packages are used to deal with images. The output will be the input frame with annotations

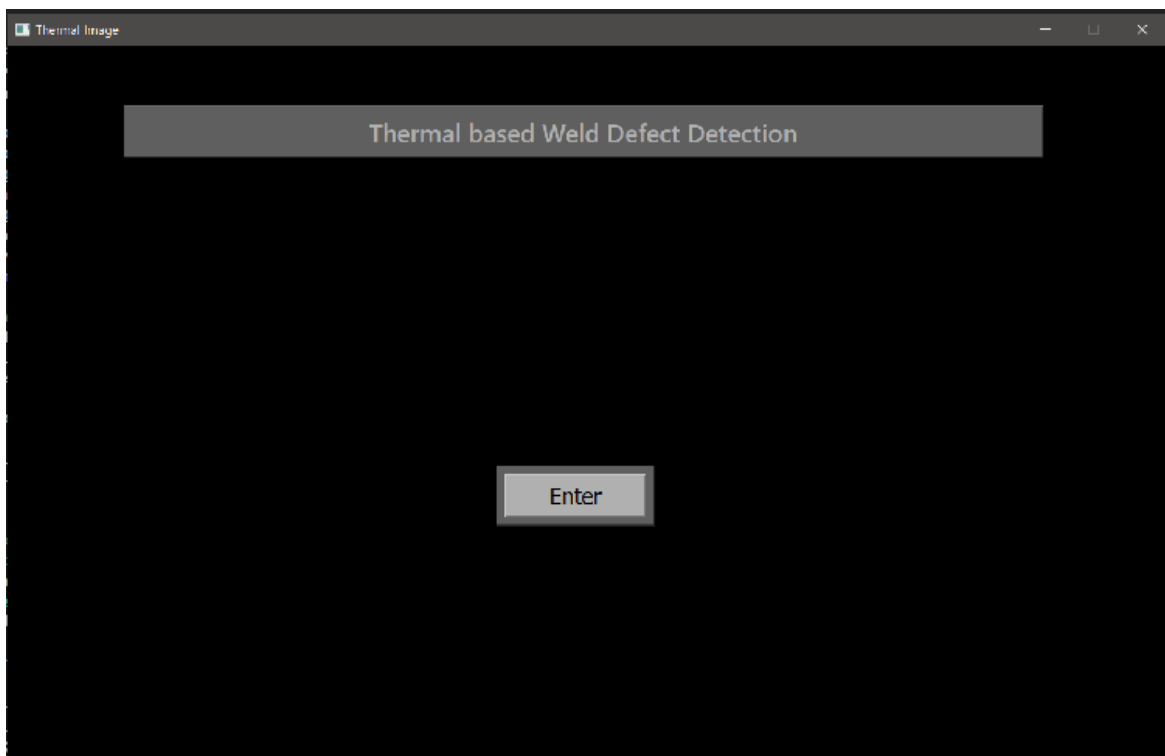


Fig:4.4: Introduction Page

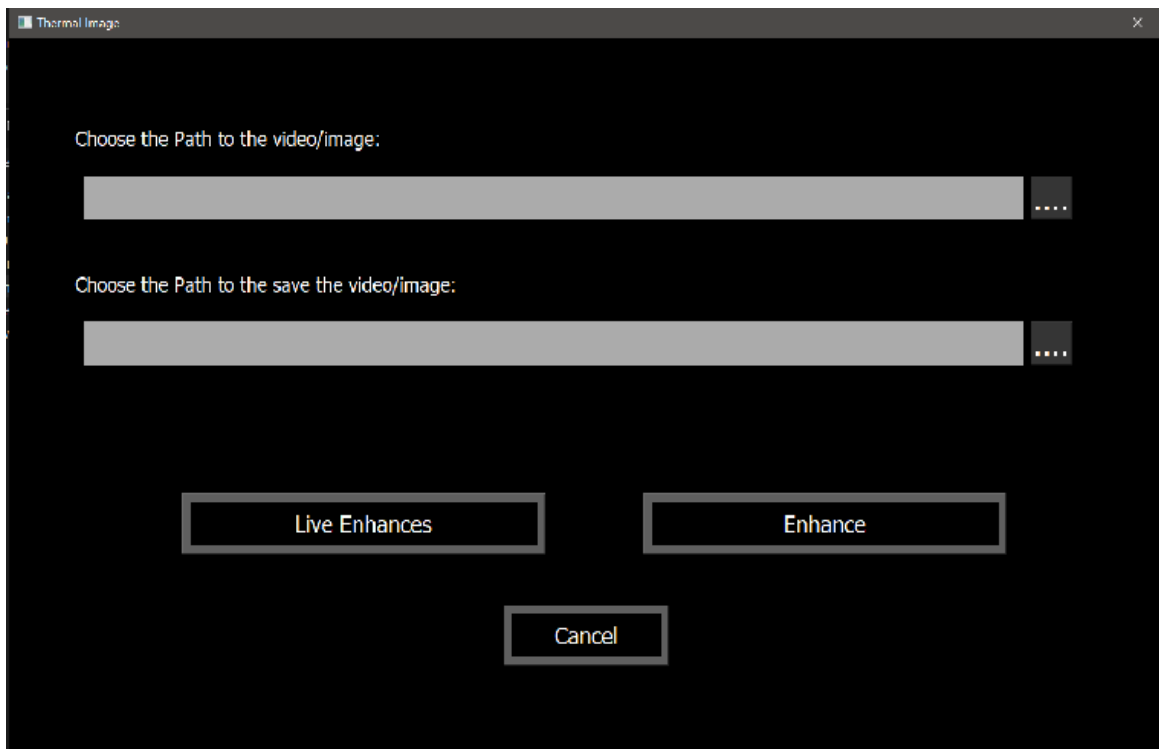


Fig:4.5: Selection Page

4.3 TRAINING THE MODEL

Here all the preprocessing of the image such as resizing, augmenting images are done and the images are fed into the model that we selected and trained for several epochs. After that, the model is connected to the GUI and used to predict the types of defects

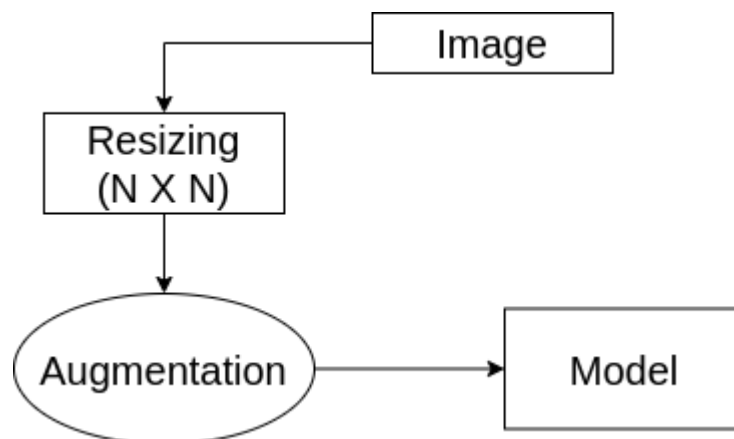


Fig:4.6: Flowchart of Prediction process

4.3.1 Data Augmentation:

Data augmentation is a technique used in machine learning and computer vision to increase the size and diversity of a dataset by creating new, synthetic data from the existing data. This technique is used to address the problem of overfitting, where a model learns to memorize the training data instead of learning to generalize to new data. The process of data augmentation involves applying a set of transformations or modifications to the existing data to create new, artificial data. These transformations can include rotating, scaling, cropping, flipping, or adding noise to the images, among other techniques.

One of the primary benefits of data augmentation is that it allows for a larger and more diverse dataset, which can improve the performance of the model. For example, in image classification tasks, data augmentation can help the model learn to recognize objects from different angles, orientations, and lighting conditions, which makes the model more robust and accurate.

The process of data augmentation can be broken down into several steps:

- **Data Collection:** The first step is to collect a representative sample of the data that the model will be trained on. This dataset should be diverse and contain enough data points to train the model effectively.
- **Data Preprocessing:** Before applying data augmentation, it is essential to preprocess the data to ensure that it is consistent and suitable for the model. This step can include resizing, normalization, and removing any irrelevant features from the data.
- **Define Transformations:** The next step is to define a set of transformations that will be applied to the data to create new, synthetic data points. This can include rotations, translations, scaling, cropping, flipping, and adding noise to the data.
- **Apply Transformations:** The transformations are then applied to the data to create new, synthetic data points. This can be done using a variety of techniques, including random cropping, random flipping, and random rotation.

- **Combine Data:** The new, synthetic data points are then combined with the original data to create a larger and more diverse dataset.
- **Train Model:** The final step is to train the model on the augmented dataset. This can be done using a variety of machine learning algorithms, including neural networks, decision trees, and support vector machines.

There are several tools and libraries available for data augmentation, including OpenCV, TensorFlow, and Keras. We used Albumentations library for it and the types of augmentations we've implemented are given below:

Table :4.1: Data Augmentation Parameters

Technique	Parameters
Grid Distortion	Num steps=4, distort limit=0.02
Optical Distortion	Distort limit=2, shift limit=0.5
Elastic Transform	Alpha=1, sigma=50, Alpha Affine=50
Brightness	limit=0.3, p=1
Hue Saturation Value	Hue shift limit=20, sat shift limit=50, val shift limit=50
Shift Scale Rotate	Shift limit=0.06, Scale limit=0.1, rotate limit=90
ISO Noise	Color shift=(0.03, 0.06), intensity=(0.3, 0.6)
Blur	Blur limit=3
Distort	grid=(3, 3)

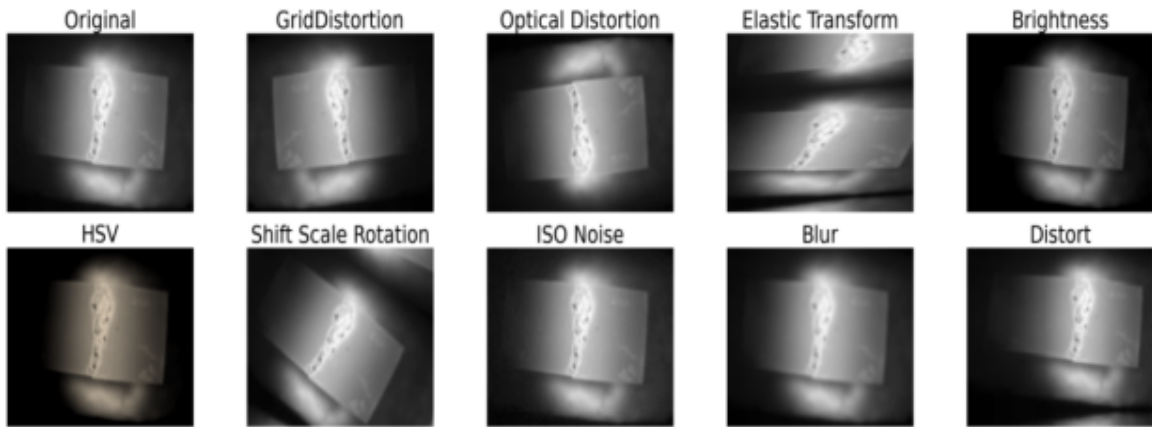


Fig :4.7: Applied Augmentation Techniques

4.3.2 Algorithm used:

The U-Net architecture is a deep learning architecture that was originally developed for medical image segmentation tasks. It has since been applied to a variety of semantic segmentation tasks and is known for its ability to effectively segment small objects and maintain spatial information. The contracting path and the expanding path are the two fundamental parts of the U-Net paradigm. The convolutional layers that make up the contracting path increase the feature mappings while decreasing the spatial dimension of the input image. We will receive a compressed version of the input image as a result. The high-level features from the contracting path are kept while a sequence of up-sampling layers and concatenation layers increase the spatial dimension of the feature maps in the expanding path.

The U-Net model is known for its skip connections, which connect the contracting path and the expanding path that allow the high-level features from the contracting path to be combined with the up-sampled feature maps in the expanding path. This helps to preserve the spatial information of the input image and results in a more accurate segmentation. The final output of the U-Net model is a segmentation mask that highlights the regions of interest in the input image. The model can be trained on large annotated datasets and fine-tuned to the specific task at hand. The U-Net architecture is known for its ability to handle large amounts of data and to effectively segment small objects and details in images.

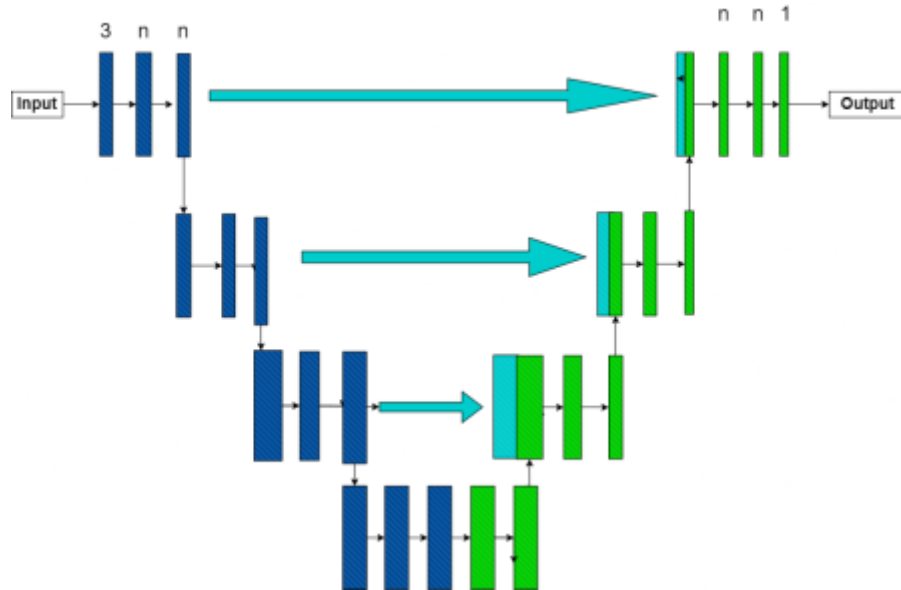


Fig:4.8: Basic U-NET Architecture

4.3.3 Backbone of Network:

Over the past couple of years using the pre-trained models as backbone network to extract features became popular. In this paper we experimented with several models like, VGG, ResNet as our backbone networks to extract features. These models are trained on ImageNet datasets. The backbone network refers to the core part of the network that performs the feature extraction process. The backbone network is responsible for learning a set of feature representations from the input data that are relevant to the task at hand, such as object recognition or semantic segmentation. These features are then passed on to subsequent layers in the network for further processing and classification. The backbone defines how the layers in our U-NET will be arranged in the encoder network and decoder. Widely used backbone networks are VGG, ResNet, EfficientNet , etc. The choice of backbone network architecture can have a significant impact on the performance of a CNN. There are several popular backbone network architectures.

4.3.4 AlexNet

AlexNet is a convolutional neural network (CNN) architecture that was developed by Alex ,Ilya, and Geoffrey Hinton. It is one of the most influential deep learning

models, as it achieved significant improvements in image classification accuracy in the ImageNet Large Scale Visual Recognition Challenge.

The AlexNet architecture consists of eight layers, including five convolutional layers, two fully connected layers, and one softmax layer. The convolutional layers use small filters (3x3 and 5x5) with a stride of 1 and are followed by max-pooling layers to reduce the spatial dimensions of the output. The fully connected layers use a rectified linear activation function and dropout regularization to reduce overfitting.

One of the key innovations of AlexNet was the use of GPU acceleration to train deep neural networks. This allowed the network to be trained much faster than previous models, which relied on CPUs for computation. Additionally, AlexNet used data augmentation techniques such as random cropping and horizontal flipping to increase the amount of training data and reduce overfitting.

AlexNet achieved state-of-the-art performance on the ImageNet dataset, with a top-5 error rate of 15.3%, significantly outperforming previous models. It also helped to popularize deep learning and convolutional neural networks, leading to further advances in computer vision and other fields of artificial intelligence.

4.3.5 VGG

VGG is a deep convolutional neural network architecture for image classification, developed by researchers at the University of Oxford in 2014. It is named after the Visual Geometry Group, the research group at Oxford that developed it. The VGG architecture consists of a series of convolutional layers, followed by max pooling layers to downsample the spatial dimensions of the output. The network uses small filters (3x3) with a stride of 1, and deeper layers have more filters. The number of filters in each layer doubles after each max pooling layer.

VGG also includes fully connected layers at the end of the network to perform classification. The fully connected layers use a rectified linear activation function and dropout regularization to reduce overfitting. One of the main contributions of VGG was its simplicity and uniformity. The architecture is easy to understand and modify, and the use of small filters with a stride of 1 allows for more precise control

over the feature maps. Additionally, VGG achieved state-of-the-art performance on the ImageNet dataset, with a top-5 error rate of 7.3%, significantly outperforming previous models.

4.3.6 ResNet

ResNet (Residual Network) is a deep neural network architecture for image classification, developed by researchers at Microsoft Research Asia in 2015. It is designed to address the problem of vanishing gradients in deep neural networks, which can make it difficult to train very deep architectures. The ResNet architecture introduces residual connections, which allow the network to learn residual functions that can be added to the output of previous layers. This makes it easier for the network to learn the identity function and also allows the network to be much deeper than previous architectures. The residual connections are achieved by using skip connections that bypass one or more convolutional layers. This allows the output of earlier layers to be added directly to the output of later layers, creating a "shortcut" that allows the network to learn a residual function.

ResNet is typically implemented using convolutional layers with small filters (3x3) and a stride of 1. The network also uses batch normalization and rectified linear activation functions. The residual connections are added every few layers, with the exact number of layers between the residual connections varying depending on the specific implementation. ResNet achieved state-of-the-art performance on the ImageNet dataset, with a top-5 error rate of 3.57%, significantly outperforming previous models. It has since been used as a baseline architecture for a wide range of computer vision tasks, including object detection, semantic segmentation, and transfer learning. The use of residual connections has also inspired new architectures for other types of neural networks, such as recurrent neural networks.

4.3.7 EfficientNet

EfficientNet is a deep neural network architecture for image classification, developed by researchers at Google in 2019. It is designed to achieve state-of-the-art performance with significantly fewer parameters and FLOPS (floating-point operations per second) compared to other architectures. EfficientNet

achieves its efficiency by using a combination of compound scaling, which scales up the network while controlling the number of parameters and computational cost, and a new type of block called the "Mobile inverted bottleneck block".

The Mobile inverted bottleneck block consists of three layers: a depthwise convolution, a pointwise convolution, and another pointwise convolution with a linear activation function. This block is inspired by the MobileNet architecture, but with an inverted bottleneck design that allows the network to learn more complex representations. EfficientNet also uses a novel approach to scaling the network, which involves increasing the depth, width, and resolution of the network simultaneously. This approach ensures that each new layer has enough computational capacity to learn more complex features.

EfficientNet achieved state-of-the-art performance on the ImageNet dataset, with a top-1 accuracy of 84.3% and a top-5 accuracy of 97.0%, while using significantly fewer parameters and FLOPS compared to other models. It has since been used as a baseline architecture for a wide range of computer vision tasks, and has inspired new approaches to designing efficient neural networks.

4.3.8 Seresnet

Seresnet (Squeeze-and-Excitation Residual Network) is a deep neural network architecture for image classification, developed by researchers at the Chinese Academy of Sciences in 2018. It builds on the ResNet architecture by introducing a new type of block called the "Squeeze-and-Excitation block", which allows the network to selectively emphasize important features. The Squeeze-and-Excitation block is added to each residual block in the network and consists of two operations: a squeeze operation and an excitation operation. The squeeze operation reduces the spatial dimensions of the input tensor, while the excitation operation models the interdependencies between the channels of the squeezed tensor.

The squeeze operation is achieved by using a global average pooling layer, which computes the average value of each channel of the input tensor. This results in a $1 \times 1 \times N$ tensor, where N is the number of channels. The excitation operation then applies two fully connected layers with a sigmoid activation function to model the

interdependencies between the channels. The output of the excitation operation is a $1 \times 1 \times N$ tensor, which is multiplied with the input tensor to selectively emphasize important features.

4.3.9 SE-ResNeXt

SE-ResNeXt (Squeeze-and-Excitation ResNeXt) is a deep neural network architecture for image classification, developed by researchers at the Chinese Academy of Sciences in 2018. It builds on the ResNeXt architecture, which is a variation of the ResNet architecture that uses a group of convolutional layers in parallel to learn more diverse feature representations.

SE-ResNeXt introduces the Squeeze-and-Excitation block to the ResNeXt architecture, allowing the network to selectively emphasize important features across different groups of convolutional layers. The Squeeze-and-Excitation block is added to each group of convolutional layers and operates on the output of the group. This allows the network to selectively emphasize important features both within each group and across different groups.

The Squeeze-and-Excitation block operates in a similar way to the one used in the SE-ResNet architecture. It first squeezes the spatial dimensions of the input tensor using global average pooling, then uses two fully connected layers with a sigmoid activation function to model the interdependencies between the channels. The output of the excitation operation is then multiplied with the input tensor to selectively emphasize important features. SE-ResNeXt achieved state-of-the-art performance on several image classification benchmarks, including ImageNet, CIFAR-10, and CIFAR-100. It has since been used as a baseline architecture for a wide range of computer vision tasks, and has inspired new approaches to designing neural networks that selectively emphasize important features across different groups of convolutional layers.

4.3.10 DenseNet

DenseNet (Dense Convolutional Network) is a deep neural network architecture for image classification, developed by researchers at Facebook AI Research in

2016. It builds on the idea of skip connections introduced in the ResNet architecture, but takes a different approach to connect layers in the network.

In DenseNet, each layer is connected to every subsequent layer in a dense block, forming a densely connected network. This means that the output of each layer is concatenated with the output of all the previous layers in the block, creating a dense feature map. The resulting feature map is then fed into the next layer in the block, which in turn is connected to all subsequent layers in the block.

DenseNet also includes transition layers, which reduce the spatial dimensions and the number of feature maps between the dense blocks. The transition layers consist of a batch normalization layer, followed by a 1x1 convolutional layer and a 2x2 average pooling layer. DenseNet's densely connected architecture allows the network to reuse features more effectively, which reduces the number of parameters and helps to combat the vanishing gradient problem. It also improves the gradient flow through the network, which makes it easier to train deeper networks.

4.3.11 Loss Function:

The Loss function we used is the combination of sparse categorical cross entropy and Dice loss with the weight age 1:1.5 and Two Metrics were used to monitor the accuracy of the model - F1 Score and IoU

4.3.12 Hyperparameter Tuning:

For training the models. We resize the images into 128 X 128 and performed semantic segmentation. As the pixel distribution for Excessive Reinforcement is high and the others are not evenly distributed, Data Augmentation is done. Instead of down weighting the category with dominant pixel distribution, Categorical Focal Loss is used . The model is trained on GPU Tesla P100 (16 GB RAM).

- Adam Optimizer - learning rate = $1e-3$; Beta 1 = 0.99
- Batch Size = 32
- Epochs = 100 with learning rate scheduler and early stopping which monitors the Intersection over Union values
- Activation Function = Softmax

CHAPTER 5

RESULTS, DISCUSSIONS AND PERFORMANCE ANALYSIS

The following discusses the results and performance analysis of our model of the dataset.

5.1 EVALUATION METHODS

As we mentioned in previous chapters we use a combination of two loss functions to train our model and we use two different metrics to check the performance of our model on the train and test data. Let's go through the loss function and metrics first.

5.1.1 Loss

In deep learning, the loss function is a crucial component of the training process, which measures the difference between the predicted output and the true output. The loss function serves as a guide for the optimization algorithm to adjust the model's parameters to minimize the difference between the predicted output and the true output. The choice of the loss function depends on the type of problem being solved, such as classification or regression, and the specific requirements of the application.

For classification problems, the most commonly used loss function is the cross-entropy loss, which measures the difference between the predicted probabilities and the true labels. The cross-entropy loss penalizes the model more for incorrect predictions with high confidence and less for incorrect predictions with low confidence, encouraging the model to make more confident and accurate predictions.

For regression problems, the mean squared error (MSE) loss is a commonly used loss function, which measures the difference between the predicted values and the true values. The MSE loss penalizes larger errors more heavily than smaller errors, encouraging the model to make more accurate predictions.

Other loss functions, such as the hinge loss and the focal loss, are used for specific tasks, such as binary classification and object detection, respectively. The choice of the loss function can significantly impact the performance of the model. The loss function we chose is the combination of sparse categorical cross entropy and Dice loss with the weightage 1:1.5.

Sparse categorical cross entropy is a loss function used in deep learning for multi-class classification problems where the true labels are integers representing class indices rather than one-hot encoded vectors. It measures the difference between the predicted probabilities and the true class indices and penalizes the model more for incorrect predictions with high confidence. The sparse categorical cross entropy is a variant of the categorical cross entropy loss function, which is used when the true labels are one-hot encoded vectors. The use of sparse categorical cross entropy reduces the memory requirements and computational complexity of training the model.

$$L_{CE} = - \sum_{i=1}^n t_i \log(p_i)$$

Fig:5.1: Sparse Categorical Cross-entropy

Dice loss is a loss function used in deep learning for image segmentation tasks. It measures the overlap between the predicted segmentation mask and the true segmentation mask using the Dice coefficient, which is a similarity metric between two sets. The Dice loss function penalizes the model more for incorrect predictions in regions where the overlap between the predicted mask and the true mask is low. The use of Dice loss is common in medical image analysis tasks where accurate segmentation is critical, and the class imbalance between the foreground and background regions is significant.

$$D = \frac{2 \sum_i^N p_i g_i}{\sum_i^N p_i^2 + \sum_i^N g_i^2}$$

Fig:5.2: Dice Loss

5.1.2 Metrics

Metrics in deep learning are used to evaluate the performance of a model during training and testing. Metrics are numerical measures that quantify the quality of the model's predictions, such as accuracy, precision, recall, F1 score, and mean squared error. Accuracy is a common metric used for classification tasks, and it measures the percentage of correctly predicted labels. Recall gauges the percentage of real True positives among actual positives, while precision gauges the percentage of True positives among actual positives. The F1 score strikes a compromise between recall and precision, and it is particularly helpful when the proportion of positive and negative examples is unbalanced.

For regression tasks, the mean squared error (MSE) is a common metric that measures the average squared difference between the predicted values and the true values. Other metrics used in regression tasks include mean absolute error (MAE) and root mean squared error (RMSE). Metrics are used to compare different models and hyperparameter configurations and to track the progress of the model during training. The choice of metrics depends on the task and the specific requirements of the application. In addition to the standard metrics, researchers often define custom metrics tailored to the specific problem domain.

F1 score is a metric used in machine learning to evaluate the performance of binary classification models, where the goal is to classify inputs into one of two classes, usually referred to as positive and negative. The F1 score is a weighted harmonic mean of precision and recall, and it ranges from 0 to 1, with 1 being the best possible score.

Recall gauges the percentage of real True positives among actual positives, while precision gauges the percentage of True positives among actual positives. The F1 score strikes a compromise between recall and precision, and it is particularly helpful when the proportion of positive and negative examples is unbalanced.

$$F_1 = \frac{2 * Precision * Recall}{Precision + Recall}$$

Fig:5.3: F1 Score

A high F1 score indicates that the model is performing well on both precision and recall, which means that it is making accurate predictions while minimizing false positives and false negatives. The F1 score is a useful metric when the cost of false positives and false negatives is similar. However, in some cases, such as medical diagnosis, the cost of false negatives may be significantly higher than the cost of false positives, and in such cases, the F1 score may not be the most appropriate metric to use.

In computer vision and image segmentation tasks, the measure known as intersection over union (IoU) is frequently used to assess the degree of overlap between anticipated and real-world bounding boxes or segmentation masks. The Jaccard Index is another name for it. IoU is calculated as the intersection of the projected and real world regions' intersection and union areas. The IOU ranges from zero to one, where zero denotes no overlap and 1 denotes a perfect overlap

IoU is often used as a performance metric for object detection and instance segmentation tasks. A high IoU indicates that the predicted bounding box or segmentation mask accurately represents the ground truth region. In addition to being used as a metric for evaluating models, IoU is also used in the training process as a loss function, where the goal is to maximize the IoU between the predicted and ground truth regions.

$$IoU = \frac{TP}{(TP + FP + FN)}$$

Fig:5.4: IoU

We demonstrate the application of our model to the training dataset of segmentation tasks in Table 5.1. Implementation of U-NET with seresnet101 as background performed better, obtaining 0.7703 F1 Score and 0.7215 Mean IoU 0.2502 loss.

Table :5.1: Results of training data

Model	Loss	F1 Score	Mean IoU
EfficientNetB0	0.4400	0.605	0.56
EfficientNetB5	0.4415	0.6119	0.5462
EfficientNetB7	0.3111	0.7084	0.6308
VGG19	0.4138	0.6483	0.5793
seresnet101	0.2502	0.7703	0.7215
Densenet201	0.32	0.6945	0.6173
Seresnext101	0.38	0.6156	0.6124
Resnet152	0.37	0.664	0.579

We demonstrate the application of our model to the test dataset of segmentation tasks in Table 5.2. Implementation of U-NET with seresnet101 as background performed better, obtaining 0.7615 F1 Score ,0.742 Mean IoU and 0.241 loss.

Table :5.2: Results of test data

Model	Loss	F1 Score	Mean IoU
EfficientNetB0	0.4325	0.612	0.63
EfficientNetB5	0.4480	0.6012	0.5368
EfficientNetB7	0.3083	0.6789	0.6065
VGG19	0.412	0.645	0.575
seresnet101	0.241	0.7615	0.742
Densenet201	0.2882	0.7279	0.651
Seresnext101	0.329	0.7215	0.64
Resnet152	0.33	0.6998	0.617

Let's look at the difference between the predicted mask and original mask of the images and also the confusion matrix which shows how well the pixel prediction is in our model below.

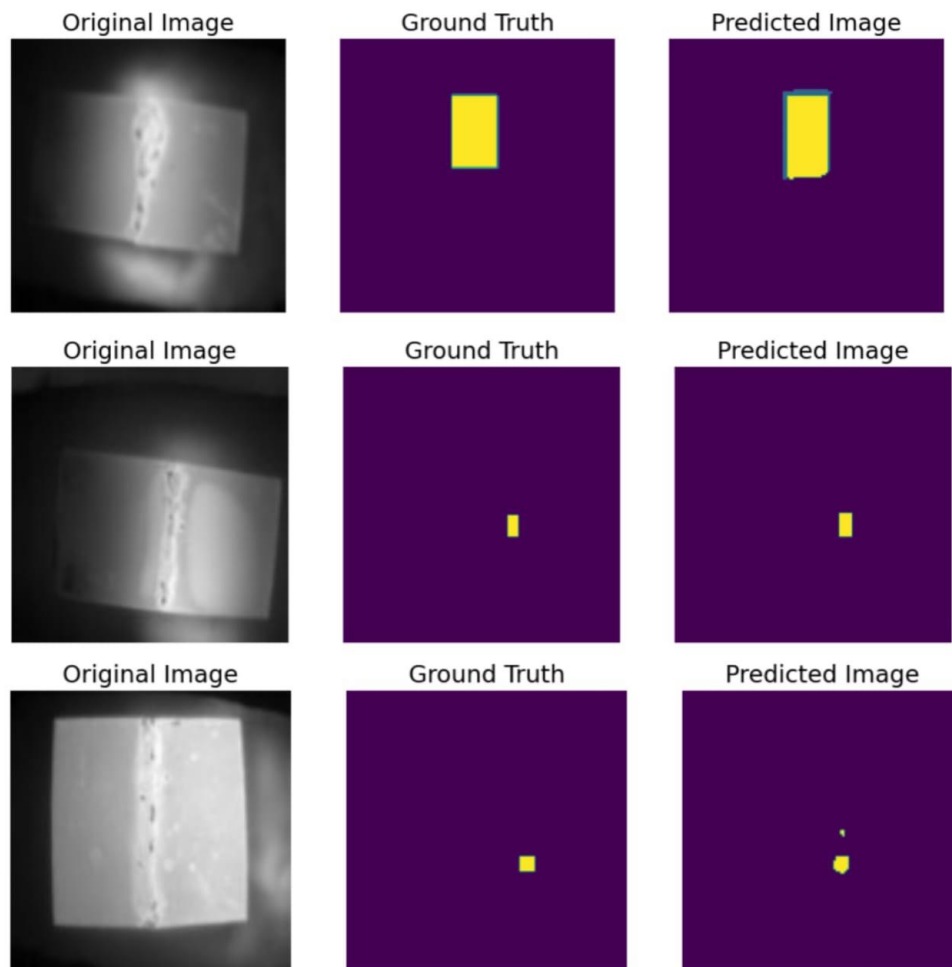


Fig:5.5: Ground truth and predicted mask

The model puts out the decent result and now let's check the confusion matrix. A confusion matrix is a table used to evaluate the performance of a machine learning classification model. It shows the number of true positives, false positives, true negatives, and false negatives predicted by the model for each class. The rows of the matrix correspond to the actual class labels, while the columns correspond to the predicted class labels.

The confusion matrix helps to evaluate the accuracy of the model by showing how well it correctly predicts each class. The confusion matrix is particularly useful when dealing with imbalanced datasets, where the distribution of class labels is not equal, as it helps to identify where the model is making errors and which classes are more difficult to predict.

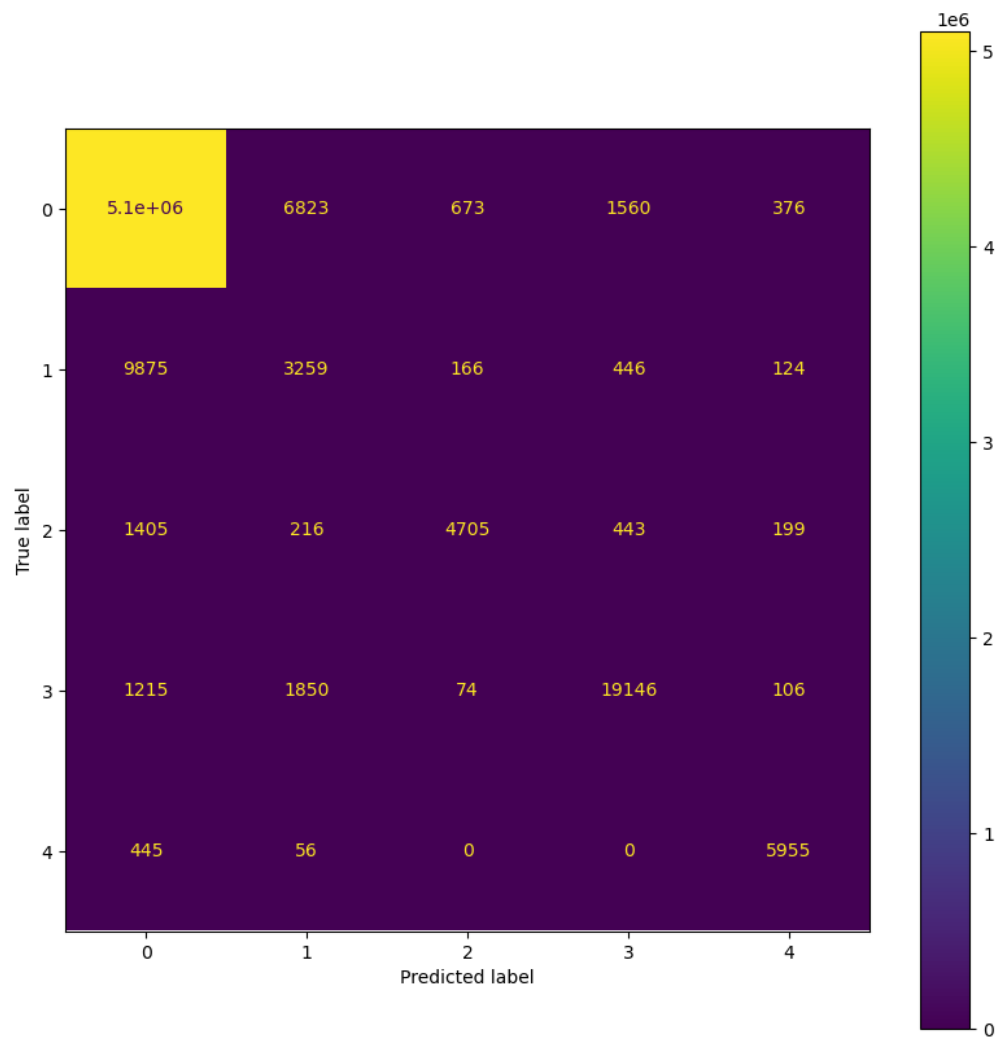


Fig:5.6: Confusion matrix

CHAPTER 6

SUMMARY AND CONCLUSION

Semantic segmentation is a computer vision task that involves assigning a class label to each pixel in an image. Deep learning models such as Convolutional Neural Networks (CNNs) are often used for this task due to their ability to learn complex visual patterns. The Summary of the whole process goes from Data Preparation to software creation.

Data preparation: First we used FLIR LEPTON and Raspberry PI to extract thermal images.

Data Augmentation: In this step we added several augmentation techniques using albumentations library to generate more samples by adding additional effects such as blur, contrast, e.t.c.

Model selection: Several backbone architectures are explored for our U-NET model and seresnet101 model as backbone is selected.

Hyperparameter Tuning : Once the architecture is selected, several hyper parameters are tuned to get better results.

Loss function selection: The loss function is used to measure the difference between the predicted and actual class labels. We used F1 Score and Dice loss with certain weightages.

Validation: After training, the model is evaluated on the validation set to measure its performance.

From Result table, we can see that seresnet 101 performs better with less number of data with the help of augmentation techniques with 0.241 (Categorical Focal Loss+Dice Coefficient Loss), 0.7615 F1 Score and 0.742 Mean IoU in the testing data. We achieved pixel accuracy of 99.2 percent.

The results are promising and show the potential for incorporating UNET segmentation with backbones to assist the defect detections in welding. One of the limitations or drawbacks of this process is that the uneven distribution of pixels for each category and With more data and wide number of defect types collected the neural networks can potentially improve the quality, time and consistency of defect detections in welding.

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ANNEXURE:

- Review paper on the title of “Automatic detection of defects in welding using deep learning - a systematic review by M. Amarnath, N. Sudharshan, P. Srinivas has been presented in iCAM conference conducted by Sathyabama Institute of Science and Technology, Chennai on November 4th, 2022.
- Review paper on the title of “Automatic detection of defects in welding using deep learning - a systematic review by M. Amarnath, N. Sudharshan, P. Srinivas has been published in Materials Today: Proceedings.
- Research on the title of “Defect Detection in Welding using Thermal Image and Semantic Segmentation” by M. Amarnath, N. Sudharshan, P. Srinivas has been presented in the ICDTM conference conducted by Sastra University, Thanjavur on 9th April, 2023.



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CERTIFICATE

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—◆ Mr. SRINIVAS PALANIRAJ ◆—

Student, Sathyabama Institute of Science and Technology, Chennai-600119, India has presented a paper entitled “*Monitoring and Predictive Maintenance of Copper Pipeline Using AMG8833 Thermal Sensor*”, in the second International conference on “Advancements in Materials Science and Technology – iCAM 2022”, organized by Sathyabama Institute of Science and Technology, Chennai, India in association with Alexander Dubček University of Trenčín, Slovakia, during November 02–04, 2022.

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Automatic detection of defects in welding using deep learning - a systematic review

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ABSTRACT

The large number of research studies on defect detection and classification using Deep Learning implies the demand for AI in industrial automation systems. Welding is one of the crucial processes used in various industries with diverse applications, and one of the challenges faced in welding automation is the Defect identification using Non-Destructive Testing. This paper aims to provide a systematic review on the application of defect detection in Tungsten Inert Gas Welding using Computer Vision. This study analyses and compares the existing methodologies used in the earlier days and what is being used now. In addition, this paper discuss how Convolution Neural Network(CNN), a deep learning technique can solve the problems faced by traditional machine vision and how the Vision Transformers can be incorporated to get the better results.

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1. Introduction

The main applications for Tungsten Inert Gas(TIG) Welding are pipeline based. TIG welding is widely used in many industries like aviation, sheet metal, aerospace etc. It was invented in the 1940 s to join magnesium and aluminium. Since then, it has been used for steel, copper and numerous other alloys. The major limitation of TIG Welding is it highly relies on skilled manual welders. Another challenge is the time needed to carry it out.

The use of computer vision, X-ray images are some of the methods that can be employed to overcome these restrictions. Using Defect detection algorithms and classification models, can be used to overcome the challenge of monitoring and automating the welding with high precision and consistency. This paper goes through the overview of Computer Vision, Machine Vision, Deep Learning techniques that already exist in defect detection and identification.

2. Traditional approaches

There have been many traditional approaches like determining weld penetration using ultrasonic sensors [3], Monitoring Joint

Penetration Using IR Sensing, [4]. Multi-layer Perceptron [5], Machine Vision [6] which will be looked at briefly.

2.1. Determining weld penetration using ultrasonic sensor

In order to measure the quality and integrity of the weld, penetration is the main factor that needs to be looked at. It's done here by using ultrasonic pulse echo techniques. There has also been a method where photodetectors [7] were placed to measure the back bead width of the weld. When the weld transitions to full penetration, the IR radiation from the back side of the weld passes through a step transition, which can be detected by photodetectors.

One of the drawbacks of it is that it is difficult to locate a sensor on the back side of the weldment for many weldment configurations. To overcome this, Ultrasonic Testing is used. Ultrasonic testing has been used effectively as a NDE to detect lack of fusion, cracks and porosity. It's the process of transmitting ultrasonic pulse-waves into materials to find internal defects or to characterise materials.

If the length of the wave transmitted is less than the dimension of the material, the ultrasound pulse will rearrange the phase relationship of the incident pulse and there will be some change in the ultrasound pulse which is projected and the reflected one. From that size and shape of i can be extracted.

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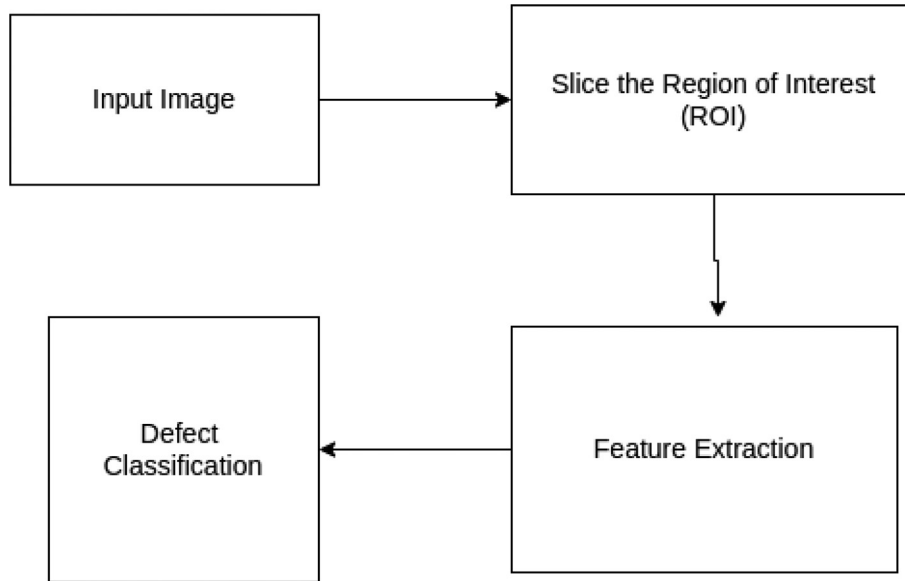


Fig. 1. Flowchart of MLP.

This method is suitable for detecting porosity and lack of penetration, But the difficulties in it is that there are difficulties in recording the reflected pulses if the material is thin. The following diagram shows the typical setup of detecting defects using an Ultrasonic sensor.

2.2. Monitoring joint penetration using IR sensing

First, an IR camera is set to monitor the surface temperature and molten pool during welding. A linear relationship exists between the infrared thermal image profile width and the bead width. There is also an exponential relationship between the depth and integrated area under the peak temperature profile [3].

2.3. Multi-layer perceptron

Multi Layer Perceptron is a fully connected dense layer which transforms the dimension of input data to the desired data. The neurons in the Multi-layer perceptron are trained with the back propagation (Fig. 1). Multilayer Perceptrons are designed to approximate continuous function.

The basic architecture of MLP consists of one input layer which receives the input, a hidden layer and an output layer which is based on the type of problem. In a single perceptron, linear problems can be resolved, but it is not well suited for non-linear cases.

To solve these complex problems, Multi-layer perceptrons are used. The weights of the network are initialised to random values. After finishing the learning process by using the training data, the model is validated.

Based on the result of validation, the optimization in Multi-layer Perceptron weights is done using the backpropagation algorithm, which attempts to reduce the error and improve the accuracy for further prediction.

3. Weld defects

The common weld defects (Fig. 2.). are discussed below.

3.1. Burn through

Burn Through happens when heat is passed more than the required amount. It causes more weld metal to penetrate the weld zone, which causes it to swell.

3.2. Contamination

Contamination happens when an external substance (oil or fumes) is accidentally introduced while welding.

3.3. Lack of fusion

Lack of fusion is a condition where the weld filler metal does not properly fuse with the base metal.

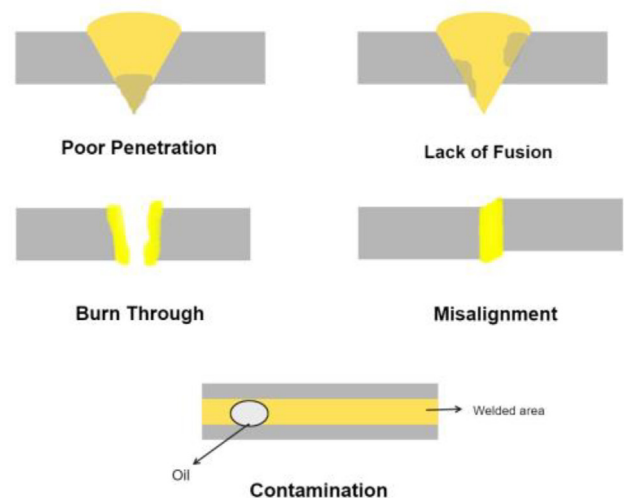


Fig. 2. Types of Defects.

3.4. Misalignment

Misalignment happens when two dissimilar metal thickness are joined or by accident. It's also called as hi-low.

3.5. Lack of penetration

Lack of penetration occurs when the weld metal does not penetrate the joint. This can occur if the adequate amount of heat is not applied.

4. Introduction to computer vision using artificial intelligence

Artificial Intelligence has been used widely in many sectors from manufacturing, production, fault diagnosis and condition monitoring[2]. They outperform traditional approaches in automation and in many industries.

4.1. Artificial intelligence

Rapid advances in the field of artificial intelligence revolutionized many fields such as computer vision, Natural Language processing and Recommender System. Recently, AI is solving complex problems in various domains consistently with high precision. AI can mimic human intelligence up to certain limits with certain limitations at this point.

AI started to get its attention in 1989 from automatic digit recognition [8] by using convolutional neural network (CNN). Convolutional neural network (CNN) are better at extracting features from images than the other approaches.

AI is the overarching umbrella encompassing computer vision, Natural Language Processing, Reasoning, machine learning, Deep Learning, etc. A subset of Artificial Intelligence (AI) is Machine learning (ML) that allows one to make a prediction with high accuracy without explicitly programming.

4.2. Classification of Machine Learning:

- Supervised Learning
- Unsupervised Learning
- Reinforcement Learning

4.2.1. Supervised learning

Supervised machine learning creates a function for prediction based on labeled data. The training data consist of features whose characteristics are known. The correct label of the training data is given.

The training data is passed to the algorithm, and it optimizes itself and creates a function which has minimum loss. The algorithm should be able to generalize the training data in such a way that it can predict the even unseen data.

4.2.2. Unsupervised learning

Unsupervised machine learning is the formulation of a function based on unlabelled data. The algorithm scans through the entire data to discover hidden patterns or data groupings without any intervention.

Dimensionality and clustering algorithms come under this type.

4.2.3. Reinforcement learning

Reinforcement learning is a sub-field of Machine Learning which has grown enormously in the past couple of decades. It is about taking required action to increase reward in a given situation. The agent will be able to find the best suitable behaviour or

path it should take in a given situation. The agent will be able to optimize itself based on the reward it receives for the action it took.

4.3. Deep learning

Deep Learning using convolutional neural networks has been overwhelmingly successful in computer vision, and is the most common approach in detecting objects[9]. Unlike the traditional computer vision techniques, In this paper, computer vision is explored.. This paper aims to give a systematic review of the latest achievements, technique that can be incorporated into our application. In the beginning stage of computer vision development, deep learning was not preferred as it's computationally expensive.

So the computer vision researchers were only incorporating machine learning techniques like Support Vector Machine, K-Nearest Neighbour, Random Forest [24],[25] etc.

In the past two decades there has been enormous amount of development in deep learning because of the improvement in computation power which led to the development of many architectures such Convolutional Neural Networks (CNNs), Long Short-Term Memory Networks (LSTMs), Recurrent Neural Networks (RNNs), Generative Adversarial Networks (GANs), etc.

Since the extraordinary performance by the ImageNet competition, Convolutional Neural Networks has become the go-to DL methods. Few of the applications of Computer Vision are object detection and object classification. The important advantage of the CNN is that it does not need feature extraction and calculation compared to conventional methods. The CNN is made up of convolutional layers, pooling layers, and fully connected layers. In the convolutional layers, a CNN uses different kernels to convolve the full image and extract the useful features from it.

The accuracy of deep learning models prediction can be enhanced by having huge model sizes. Deeper and wider network architectures such as InceptionV1 and VGG-Net gave classification performances across applications [23].

4.3.1. Convolutional neural network

Instead of preprocessing the image to extract features from an image, raw image can be passed to CNN to learn and extract the features on its own (Fig. 3)[27]. First a 3-D image is passed as input where each dimension represents each primary colour (RGB) and the input layer is followed by a bunch of blocks which perform element wise dot product between a receptive field and a subarray of an input array (Kernel). Each kernel has its own weight which is updated for each iteration and then the multiplied values are summed, and bias is added to it. This results in a convolved feature matrix. During training, the CNN's kernel matrix optimizes its value to extract meaningful features.

One of the benefits of the convolution is that it decreases the shape of the input image, which in turn reduces computational cost. A hyperparameter called stride plays an important role in it. The stride specifies how many columns and rows of the receptive field slide at a time across the input array's height and width. Stride size is inversely proportional to the output size.

In order to introduce nonlinearity into the model, an activation function is applied. There are many types of activation functions [21].

After convolution the pooling step is carried out, where the CNN downsamples the convolved feature, reducing the number of dimensions without losing any feature information. A common pooling method used for this process is called max pooling. There are other pooling techniques like mean, average, spatial, etc.

The fully connected layer is introduced after the convolutional blocks. The output of the mentioned network's output is a 1-dimensional vector as a probability function with the total

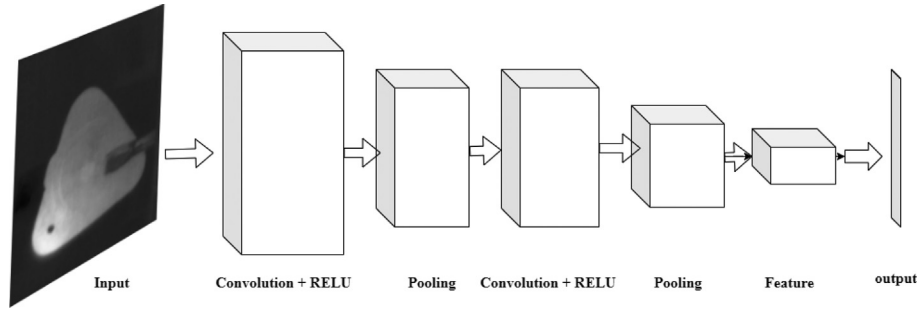


Fig. 3. An example of visualization of feature maps dimensions.

number of elements to be classified. It shows how successfully each type of class is trained and predicted using the input photos.

5. Transfer learning for defect detection

As the first layers of CNN kernels act as Colour blob detectors and filters which seems to be very general, This network can be used to identify image/object classes that it has never been trained on. Models trained on one dataset can transfer the features to another [10].

Generally speaking, deep learning for computer vision uses two types of transfer learning[13].

1. Use Pre-existing SOTA model to extract features [20].

2. Using the FC layer of our choice and replacing the fully connected layers of the pre-trained DNN model.

6. Transformers

Transformers are deep learning based models which are based on attention mechanisms. Initially it was widely used in natural language processing to solve text based problems. Later it was incorporated into solving image based problems. Vision transformer is one of the popular transformers which is good at image classification.

Transformers divide images into a grid of patches and are flattened into a one dimensional vector and linearly projecting them into a desired dimension (Fig. 4). Transformers are very good at

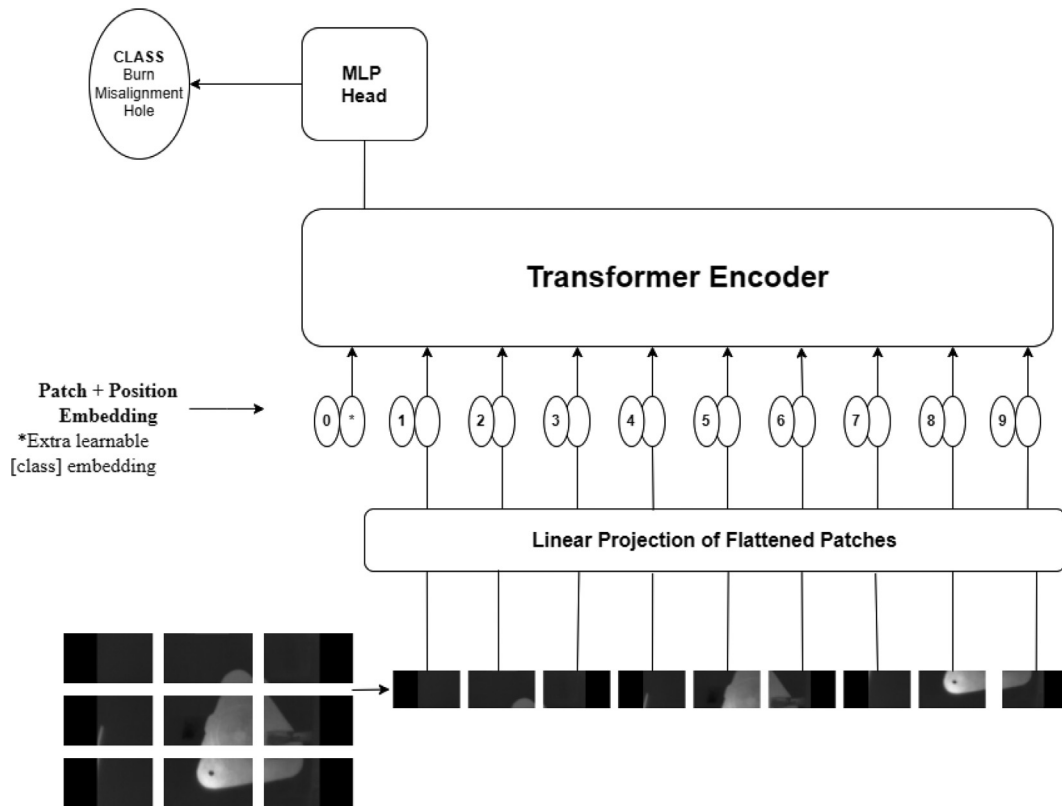


Fig. 4. Architecture of Vision Transformer.

Table 1

Results of predicted results from different pretrained models.

Model	Train Categorical Accuracy	Test Categorical Accuracy
ResNet-50	69.2	69.4
VGG-19	96.2	95.8
MobileNet	97.9	98
EfficientNet-B6	65.2	65.6
DenseNet	96.2	95.5

extracting local features in an image and in order to get the order of patched correct the position encoding is injected to input encodings[14].

7. Case study for detection of Tungsten Inert gas welding defects

This section provides an overview of the complete process of our framework, First the data is split into 3 proportions for training, validating and testing. To train a classifier, dataset with raw images with variations, such as lighting, shadow, etc., are used.

Resizing and normalization were used to preprocess of TIG welding images, Resolution of the images can be selected based on the computational power and the chosen transfer learning approach (like 224 X 224 or 512 X 512). A CNN is fed with predefined training image collection, Either a custom architecture can be created or SOTA architecture like VGG, ResNet, DenseNet, etc can be created.

Once the CNN classifier has been validated, based on its performance parameters like changing activation function, changing pooling techniques, filter size, etc are tweaked, or State of the art architectures can be incorporated to get the better result. Previous research done by Daniel Bacioiu, Geoff Melton, Mayorkinos Papaelias, Rob Shaw on 6-class classification gave the highest of

Table 2

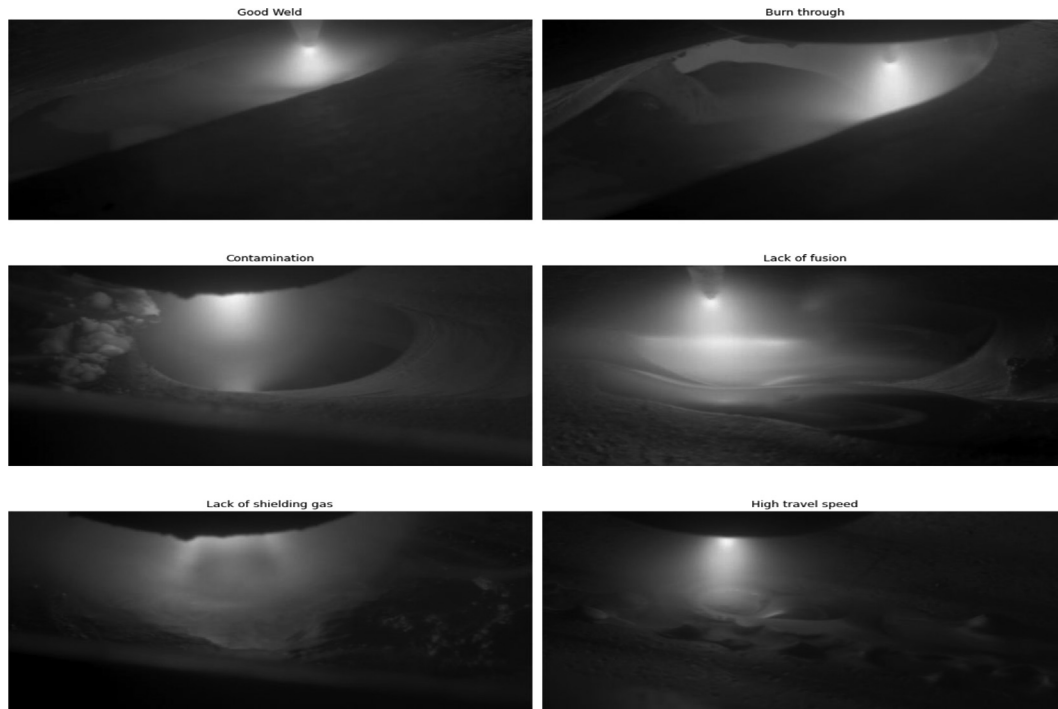
Classification Metrics Report for 6 classes.

Model	Precision	Recall	F1 Score
Good Weld	1.00	0.98	0.99
Burn Through	0.93	1.00	0.97
Contamination	0.82	1.00	0.90
Lack of fusion	1.00	0.99	1.00
Lack of shielding gas	0.91	1.00	0.95
High Travel Speed	0.92	0.98	0.95

71.22% accuracy on the custom model with the learning rate of 0.001[1]. So we used the same dataset with different transfer learning models like EfficientNet[15], DenseNet [16], MobileNet [17], VGG,[18], ResNet[19] and the results of them are given below in the tabular columns (Table 1) along with the method we approached.

Various optimizers like stochastic Gradient Descent, Adam, RMSprop were tried out and went with Adam as it provided more accuracy than the other. Learning rate of 0.01 is utilized with Learning rate scheduling. Data augmentation techniques like random vertical flip, random horizontal flip, random rotation and brightness adjustment are done to increase the accuracy of the model [22].

The dataset [1] has 5 types of defects with good weld images which are shown above (Fig. 5 - Good weld, Burn through, Contamination, Lack of fusion, Lack of shielding gas, High travel speed). The dataset was heavily imbalanced so weights for each label were assigned and categorical cross entropy was used as loss function. To combat uneven distribution of classes the training and validation classes were combined and then stratified into training and validation. The Classification report for the validation data predicted using MobileNet model are given below (Table 2, Fig. 6).

**Fig. 5.** Types of Defects predicted from the database.

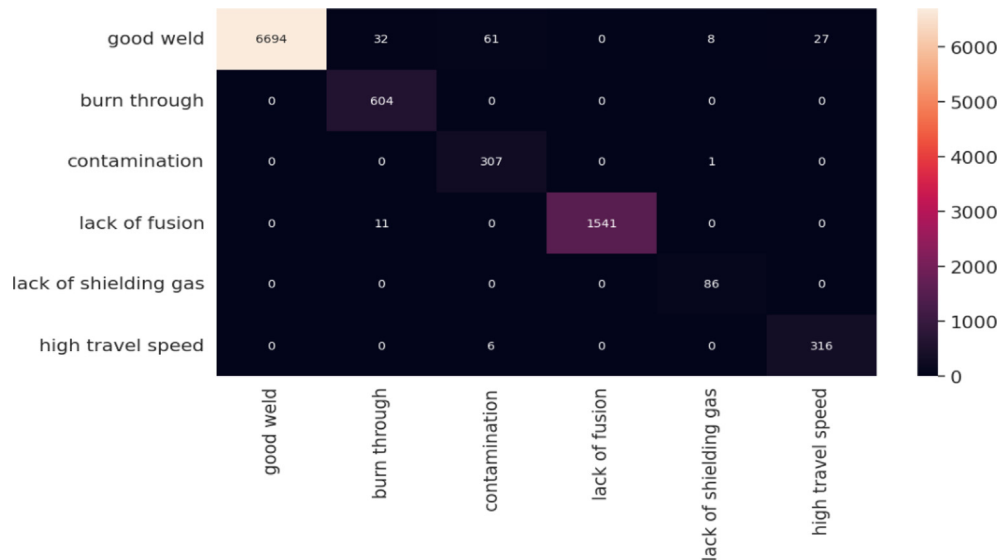


Fig. 6. Confusion matrix for predictions.

8. Conclusion

Techniques that are proposed by researchers in various domains present several innovative methodologies that can enhance the effectiveness and precision of welding defect detection. This paper compared the pre-existing technique and provided an overview of how Artificial Intelligence can improve the process of detecting the defects in welding[11]. It provides great room for improvement in sectors which requires precise welding. Coupling it with a control system can improve the profitability of industries by reducing labor costs[26].

In order for industries to adopt AI, It is necessary to improve the classification accuracy which can be improved by generating synthetic images[12], collecting new images and incorporating emerging State-of-the-Art models like transformers.

CRedit authorship contribution statement

M. Amarnath: Conceptualization, Supervision, Writing – original draft. **N. Sudharshan:** Writing – review & editing, Writing – original draft. **P. Srinivas:** Writing – original draft.

Data availability

No data was used for the research described in the article.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Defect Detection in Welding using Thermal Image and Semantic Segmentation

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Abstract. In today's world, every manual work is automated with the help of artificial intelligence. The defects in the weld are inspected manually which takes more time and the quality of inspection varies from person to person. So, automatic weld defect detection must be implemented to check every defect thoroughly without human help and in a standardized method. In this paper, we implement U-Net, a semantic segmentation model to detect various kinds of internal defects using thermal images. semantic segmentation using U-Net has the potential to significantly improve the efficiency and accuracy of welding defect detection. By automating the process, the time and resources required for inspection can be reduced, while the risk of human error is eliminated. As the technology continues to mature, it is likely that semantic segmentation using U-Net will become an essential tool for welding defect detection and analysis.

Keywords. semantic segmentation, thermal image, weld defect, u-net.

1. INTRODUCTION

Welding is a most important activity carried out in industries like automobiles where numerous amounts of parts are joined using the welding process. The welding technique most frequently employed in the industry is metal inert gas (MIG) welding. MIG welding is an arc welding process in which a continuous solid wire electrode is fed through a welding gun in between the two components to be welded. MIG welding requires three factors for an electrode to fill the metal-to-metal gap, and protect gas from pollution. They are polarity and voltage, modes metal transfer mode in MIG and welding gases.

It is important to check whether the joints have been properly welded. This process cannot be done manually in a precise as well as quick manner. so, there is a need for an automatic weld defect detection system in order to find the defects accurately and quickly. In the field of welding defect detection, semantic segmentation using U-Net has the potential to revolutionize the way that defects are detected and analyzed. The benefits of using semantic segmentation using U-Net for welding defect detection are significant. Automated inspection is faster, more consistent, and less prone to human error than manual inspection.

Semantic segmentation is a powerful computer vision technique that enables the accurate identification of objects and features within an image. U-Net is a popular deep learning architecture that has been applied to a variety of semantic segmentation tasks, including medical imaging, object detection, and scene understanding. The key to the success of semantic segmentation using U-Net in welding defect detection is the ability of the model to accurately distinguish between different types of defects, including cracks, pores, and incomplete penetration. This is achieved by training the model on large annotated datasets, where each image is labeled with the location and type of defects. The U-Net architecture, with its fully convolutional network and skip connections, is well-suited to this task, allowing for the extraction of high-level features from the input images.

This research paper [1] creates deep learning and computer vision-based model that is used to segment weld spots of iron. The Convolutional Neural Network (CNN) uses the U-Net architecture as primary and hyperparameter tuning modifications. To create the optimum model design, the use of several convolutional blocks is also investigated. The model determines the region of weld

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