Vol. 06, No. 1 (2024) 261-270, doi: 10.24874/PES.SI.24.02.009

Proceedings on Engineering Sciences

www.pesjournal.net

AUTOMATED METALLIC SURFACE FLAW INSPECTION USING ARTIFICIAL INTELLIGENCE TECHNIQUES

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Received 16.11.2023.
Received in revised form 11.01.2024.
Accepted 20.01.2024.
UDC – 004.896

Keywords:

Inspection procedure, Surface flaws, Dynamic multi-layered, Auto-encoder with robust deep, Neural network (Dmae+Dnn), Metal surface, Defect detection

A B S T R A C T

The growing demand for superior metallic components in several industries has emphasized the necessity for effective and dependable inspection techniques. Conventional manual inspection procedures are lengthy, based on personal judgment and susceptible to human mistakes. In this study, we introduce a dynamic multi-layered auto-encoder with a robust deep neural network (DMAE+DNN) system for inspecting flaws in metallic surfaces.We acquired images of the metal surface defects. The neural network design is improved by incorporating a dynamic multi-layered auto-encoder, enabling the system to obtain highly detailed representations of surface data. The results demonstrate the improved performance of the suggested system, showcasing higher levels of recall, precision and F1-score in comparison to conventional defect detection methods. This technological development has the possibility to completely transform quality control procedures by minimizing the need for manual inspections and improving the overall quality of products that heavily rely on metal elements.

1. INTRODUCTION

In the constantly shifting world of industrial manufacturing, it is of greatest importance to ensure the stability of metallic surfaces to support quality standards and avoid potential risks (Fang et al., (2020)). Traditional techniques for evaluating surface defects have been characterized by lengthy procedures, demanding physical effort and susceptible to errors made by humans. The development of advanced technology has brought a new period in quality assurance, the period of automated metallic surface defect detection (Xie et al., (2023)).

The new method integrates modern imaging technologies, artificial intelligence and robots to enhance the accuracy and effectiveness of fault identification on metal surfaces (Le et al., (2020)). Automated systems employ advanced technology such as high-quality cameras, sensors and machine learning techniques to evaluate and analyze every part of a metal surface completely. These technologies have the ability

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to detect even minute defects that can be undetected by human observation (Lv et al., (2020)).
The adoption of automated metallic surface defect detection provides numerous advantages. Initially, it reduces the inspection time, enabling producers to improve efficiency and satisfy demanding production schedules (Zhao et al., (2021)). Furthermore, the automated nature of the process minimizes the possibility of human error, providing a consistent and dependable evaluation of surface quality. This not only enhances the overall material quality but also reduces the probability of defects entering the market. An important aspect of automated metallic surface fault evaluation is its capability to function in real time, accelerating the inspection procedure (Zhang et al., (2021)). This faster evaluation enhances operational effectiveness and lowers idle time along with related expenses. The system functions without experiencing exhaustion, providing a consistent and dependable inspection process (Wan et al., (2021)).

The impacts of this technology beyond simply improvements in efficiency. Through the integration of automated inspection procedures, industries can improve and raise their overall safety requirements (Chaudhari (2021)). Recognizing possible flaws before they grow into crucial problems helps to prevent accidents and problems, ensuring the protection of human lives and expensive assets. The system's flexibility enables it to be easily incorporated into many manufacturing circumstances, ranging from the automobile and aerospace sectors to construction and other fields. This adaptability is enhanced by the capability to modify inspection criteria, adapting to the distinct requirements and regulations of various industries (Cannizzaro et al., (2021)). Traditional approaches are restricted by surface imperfections, material characteristics, lighting circumstances and algorithm accuracy. The challenges involve complicated geometries, reflective surfaces as well as varied defect sizes, which have an effect on the accuracy and dependability of inspections (Li et al., (2018)).

Anvar and Cho (2020) presented the Shuffle Defect Net, a defect detection network designed for inspecting metal surfaces. The system was the network that could acquire the precise category and exact location of a problem by combining multiple levels of information. The defect detection system was suggested to surpass the existing highest level of efficiency in defect identification, achieving a higher mean average accuracy. Sun et al., (2019) provided a new approach for inspecting surface defects. The algorithm was based on “adaptive multiscale image collection (AMIC)” and employed “convolutional neural networks.” The experimental outcomes showed the high efficacy of the suggested method in identifying different surface defects.

Li et al., (2021) designed an automated “Metro Tunnel Surface Inspection System (MTSIS)” that efficiently and accurately detects defects. The system includes the design of the hardware and software components. They suggested utilizing a “convolutional neural network” for detecting defects on the surface of metro tunnels. Their approach demonstrated superior performance compared to the most advanced techniques currently available for detecting defects on concrete surfaces. Zhou et al., (2019) explained the development and application of an innovative “automated inspection system (AIS)” for detecting surface defects in automobiles. The faults are found in or around style lines, borders and handles. The evaluation outcomes indicated that AIS detects dent faults and scratch flaws.

Boikov et al., (2021) provided a technique for training neural networks to perform visual tasks employing artificially generated input. The specific application used as an instance was the identification of defects in steel with automated manufacturing control systems. The neural networks demonstrated excellent performance in classifying and segmenting surface flaws on steel components in the image. Fu et al., (2019) presented an efficient and reliable model based on Squeeze Net for classifying defects on steel surfaces. The categorization was crucial for ensuring high-quality steel strip manufacturing and effective quality control. They obtained that their suggested method provided a considerably greater level of accuracy in recognizing defects on steel surfaces compared to the most advanced classifiers currently available.

Block et al., (2020) presented a framework for identifying moderate and severe impression flaws in printed metal parts, which was a significant issue in the automotive sector. Regarding the importance of promptly identifying severe faults, which could lead to the disposal of the printed components, the outcomes are important. Konovalenko et al., (2020) presented a novel automated technique to identify and categorize three types of surface imperfections in rolled metal. The method enables defect analysis with predetermined levels of effectiveness and speed. An evaluation was conducted on the feasibility of utilizing residual neural networks for the purpose of classifying faults. The outcomes demonstrated that the suggested models could identify surface flaws.

Liu et al., (2020) presented a new “Concurrent Convolutional Neural Network (Con-CNN)” that incorporates several image scales. The Con-CNN was designed to be efficient and practical for accurate defect detection applications. The simulation outcomes indicated that Con-CNN generated high accuracy. Guan et al., (2020) provided an enhanced deep-learning network model, utilizing feature visualization and quality assessment, which was employed to classify faults on steel surfaces. The suggested approach for classifying steel surface defects had higher accuracy and performance compared to algorithms based on VGG19 and ResNet. Ahmed et al., (2020) provided a “low-rank tensor with a sparse mixture of Gaussian” (MoG) breakdown approach for the purpose of detecting natural cracks. By utilizing a tensor decomposition structure, the suggested technique represents the sparse pattern and the low-rank tensor simultaneously. A comparison of general tensor decomposition techniques was provided. The algorithms were evaluated using “signal-to-noise ratio (SNR)” and visually compared.

Liu et al., (2023) presented an approach called “few-shot defect recognition (FSDR)” to detect flaws in metal surfaces. Attention-embedding and self-paced learning were used in the technique. The categorization information was obtained by calculating the distance of the embedded feature vector for every group. They evaluated the suggested FSDR and the investigations demonstrated comparable outcomes.

To overcome these issues, we proposed a dynamic multi-layered auto-encoder with a robust deep neural network (DMAE+DNN) for evaluating faults in metal surfaces.

1.1 Contributions

- A dynamic multi-layered auto-encoder with a robust deep neural network (DMAE+DNN) is developed for identifying flaws in metallic surfaces.
- The DMAE+DNN system deals with the problems by considerably decreasing dependence on inspections by humans.
- The study's findings show that the DMAE+DNN system outperforms existing defect detection approaches in terms of quantitative performance. Parameters such as recall, F1-score and precision demonstrate the suggested system's efficiency.

The subsequent sections of this study are structured as follows: Part 2 - Methodology, Part 3 - Results and Part 4 - Conclusion.

2. METHODOLOGY

The proposed dynamic multi-layered auto-encoder with robust deep neural network (DMAE+DNN) method are used for assessing flaws in metal surfaces. We gathered the dataset image of the defective metal surface. The dynamic multi-layered auto-encoder is utilized to detect defects in the surface and the robust deep neural network is employed to classify flaws. Figure 1 displays the flow of metal surface detection.

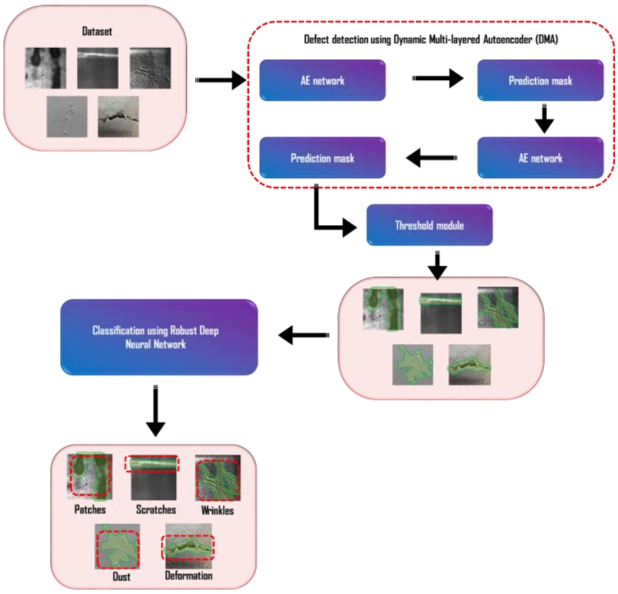

Figure 1. Flaw detection framework

2.1 Detection Component

This section provides a description of the proposed dynamic multi-layered auto-encoder design, which comprises two stages of an auto-encoder network (AEN). Information regarding the AEN and threshold module (TM) is provided in the following sections for finding defective areas.

2.1.1 Dynamic multi-layered auto-encoder architectural design

AE systems are used for encoding and decoding. An AEN has an “encoder network (EN)” and a “decoder network (DN)” with one or more decoder levels. The EN converts the “input image (II)” into a “multi-dimensional featured image” for feature separation and description. The feature maps contain helpful context. The DN utilizes contextual details from “feature maps” in every intermediary layer to improve pixel-level labelling. The DN can recover the II's initial dimensions by sampling frequently.

Metal layer flaws are local defects in a uniform appearance; therefore, flaws and background patterns indicate different properties. We use the AEN to learn about flaw representations and metal surface flaw properties. Hence, finding metal surface flaws becomes a segmentation task. The encoder-decoder design turns the II with faults into a pixel-level “prediction mask (PM)."

The dynamic multi-layered auto-encoder uses a new image segmentation structure based on two AENs simultaneously. Both AENs have identical components. Figure 1 shows that the second network uses the first network's PM. The second network refines “pixel labels.”In this way, the “second network” can enhance its forecasts. Figure 2 shows a single AEN structure. Damage patches are coloured differently due to metal surface layers. Clarity issues in this colour can affect AEN training. To minimize colour interference and speed up fault detection, the initial colour image is converted to a 512×512 grayscale image before transmission to the AEN. The encoder and decoder are on the right and left, respectively. EN and DN architectures are similar. The encoder has 10 convolution layers, each with 3×3 processes and "rectified linear unit (ReLU)" non-linear functions. The 2×2 max pooling procedure is conducted after each convolutional layer for duration of 2. To minimize the loss of semantic information, we augment the number of features by a factor of two following each max pooling layer. After each of the two convolutional layers, the decoder component utilizes a2×2 up-sampling approach. The output of the enhanced sampling procedure is merged to create the ultimate feature maps, along with a matching feature map generated during the encoder phase. At the last layer, the AEN utilizes a 1×1 convolution, this turns the outcome into a probabilistic map and continues with by a softmax layer. The ultimate probability map (PM) has been modified to align with the dimensions of the II, representing the faults.

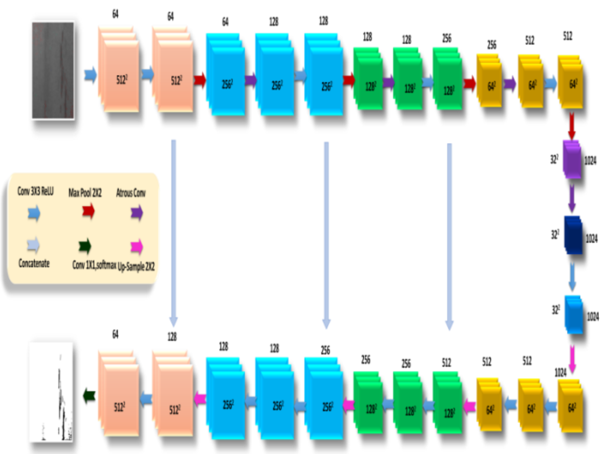

Figure 2. The AEN structure (https://www.researchgate.net/figure/Basic-architecture-of-a-single-layer-autoencoder-made-of-an-encoder-going-from-the-input_fig3_333038461)

The above AEN exhibits stable convolution ranges. This network has challenges in seeing the complete defect and incorporating a holistic circumstance to generate the PM. In a realistic industrial evaluation atmosphere, the flaws exhibit a diverse range of sizes and shapes. The above network lacks the ability to recognize the presence of larger particles, such as dust and patches, on the metallic surface. Thus, it is necessary to create receptive fields of varying sizes to manage this condition. This research utilizes atrous convolution (AC) to enhance the receptive fields of the network to discover significant faults. Figure 3 displays regular 3×3 convolutions on the left side. The AC, by a factor of two, is located on the right side. AC provides spacing between the pixels that are combined during the convolution process while maintaining the same set of pixels for summation as ordinary convolutions. The AC in the blank has weights that are set to zero, meaning they do not contribute to the convolutional process. Their receptive field is effectively 7×7. The standard convolutions in the encoder component of the AEN are changed with AC, which has a padding of 1 and a stride of 1. Table 1 displays the specific characteristics of the AC in the AE system. The encoder phase incorporates AC to substitute the four convolutional levels.

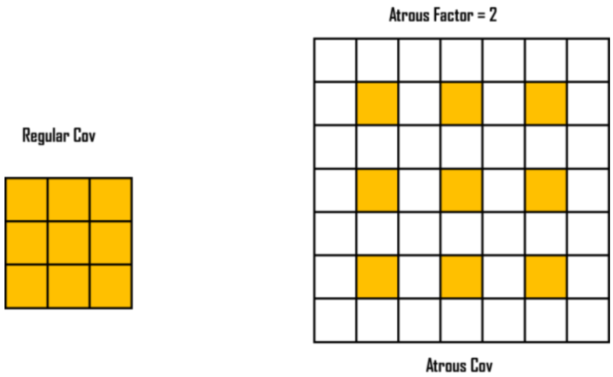

Figure 3. Atrous convolution model. (https://www.researchgate.net/figure/Atrous-convolution-diagram-with-different-atrous-rates-including-r-1-r-2-and-r-3_fig5_348078198)

Table 1. AC variables in the AEN

Convolutional Layer Index	Atrous Factor	Receptive Field Size
3	2	7 × 7
5	2	7 × 7
7	4	15 × 15
9	4	15 × 15

An enhanced "pixel-wise cross-entropy loss function" with weight x_l is developed for the purpose of training the AEN. Usually, an image taken of a metallic surface contains a greater number of background pixels compared to damaged pixels, as shown in Eq. (1). The loss function is established by incorporating classes $x_{defects} = 0.8$ and $x_{background} = 0.2$ to address the problems of imbalanced classes.

$$K_{seg} = \sum_{j=1}^{N} \sum_{i=1}^{M} \sum_{l=1}^{L} -x_l 1\left(z_j^i = l\right) \log o_l\left(w_j^i\right) \quad (1)$$

The weight is denoted by x_l, the amount of classes by $l = 2$, the "mini-batch size" of the sample used for "training" by N, the number of pixels in every image patch by M, the indicator function $1(z = l)$ (which returns 0 in the absence of $z = l$), the i^{th} pixel in the j^{th} image patch by w_j^i, the ground-truth label of w_j^i by z_j^i and the possibility that pixel $o_l\left(w_j^i\right)$, the result of the softmax layer, is the l^{th} class is represented by w_j^i.

2.1.2 Threshold Module (TM)

The TM is incorporated as a distinct module at the conclusion of the dynamic multi-layered auto-encoder network, employed to enhance the precision of the PM outcome. It has the capability to perform a “pixel-wise threshold” function on the “probability map.”This work assigns a certain TM, denoted asH_t, to the final PM, as shown in Eq.(2).

$$J_e = \begin{cases} 0, & if J_{on}(w,z) \leq H_t \\ 1, & if J_{on}(w,z) > H_t \end{cases} \quad (2)$$

J_e Represents the finial image obtained following binarization, whereas J_{on} represents the PM image and J_{on} denotes the refined threshold. During the training of dynamic multi-layered auto-encoder, the threshold that requires adjustment in the inspection architecture isJ_{on}. In imageJ_e, pixels with a grey value of 0 indicate the presence of a defect, whereas pixels with a grey value of 1 indicate the absence of any defects. The pixels in the damaged area are coloured green on the original colour image to help with the display of discovered flaws.

2.1.3 Defective area detector

After obtaining the semantic segmentation findings for the potential flaws, we utilize blob analysis to identify precise flaw boundaries. We derive the “minimum enclosing rectangle (MER)” areas by using the flaw boundaries obtained from the “finial image”J_e. The purpose of this is that MER offers a precise representation of the fault envelope area, resulting in better precision and simplified input for the categorization component.

Considering the unpredictable positioning of the MER, we utilize an affine transformation to convert the slanted MER into a positive value. The region of interest (ROI) is defined as a positive MER and the final defective areas are obtained by cropping these ROIs from the initial image. The MERs in the original image are represented by red rectangles.

2.2 Robust deep neural network

A robust deep neural network for automated metallic surface flaw detection uses advanced methods to assess and locate metal surface flaws. This technique ensures consistent and precise fault detection by exhibiting resilience to alterations in lighting, perspective and surface characteristics.

A “Deep Neural Network (DNN)” is a type of supervised learning technique that utilizes numerous layers to develop the model. The DNN utilized is based on the concept of a feed-forward artificial neural network (ANN) with numerous hidden layers, which attempts to improve the abstraction features and boost its capabilities. The design of a DNN comprises input layers, several hidden layers and an output layer, as depicted in Figure 4. Let $A = \{a_1, a_2, \dots \dots, a_o\}$be the input vector with $n = 86$ characteristics. Similarly, the output vector $T = \{t_1, t_2\}$ contains potential values in the range of [0, 1] for detecting defects in metal surfaces. The Eq.(3) used for calculating the output of every hidden layer in U_k is as follows,

$$U_k(a) = D(b_k^Y a + f_k) \quad (3)$$

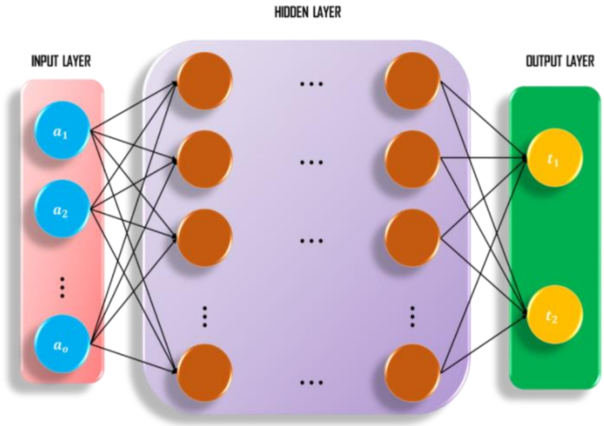

Figure 4. Structure of robust deep neural network (https://www.mdpi.com/2076-3417/11/15/7050)

Where $X(.)$ denotes the non-linear activation function, whereas b_k and f_k indicate the weight as well as bias of the hidden component$k$. The activation functions employed the ReLU for the hidden layers and a sigmoid function for the output layer. The Eq. (4&5) utilized to compute these activation parameters are as follows,

$$ReLU(a) = \max(0, a) \quad (4)$$

$$sigmoid(a) = \frac{1}{1+z^{-a}} \quad (5)$$

The DNN architecture has an input layer of 80, 32, 16 and 8 neurons, which corresponds to the numeric collection of features. We implemented four highly connected layers with 2^{10}, 2^9, 2^8 and 2^7 neurons, respectively. These are followed by a sigmoid categorization layer that produces two outputs, representing the detection of surface flaws in metals. In an instance that analyses numerical and classification characteristics, the input layer consists of five neurons. This is accompanied by two dense layers with 2^8 and 2^7 neurons, respectively. The output layer uses a function of sigmoid activation to detect flaws in the metal surfaces. In summary, reliability and effectiveness are improved by using robust deep neural networks for automated metallic surface fault detection. The model's versatility and capacity to analyze intricate data assure accurate flaw identification, enhancing the dependability and efficiency of industrial metallic surface evaluation procedures.

2.3 Dynamic multi-layered auto encoder with robust deep neural network(DMAE+DNN)

The modern method for automated metal surface fault analysis is the Dynamic Multi-Layered Auto-encoder with Robust Deep Neural Network (DMAE-DNN). The DMAE+DNN approach combines the strength of deep neural networks with dynamic auto-encoders to improve the precision and effectiveness of metallic surface defect detection.

The auto-encoder's dynamic properties enable the network to extract information and modify its internal models of the input data, resulting in persistent performance even when presented with a variety of dynamic faults. The model's strength to identify small faults that can resist standard inspection techniques is enhanced by its capacity to detect complex patterns and characteristics inherent in metal surfaces, which is made possible by using several layers in the design.

The dynamic auto-encoder element ensures that the model is robust to changing conditions in the environment by adjusting over time to evolving patterns and changes in surface flaws. In real-world situations, where metallic surfaces can experience a variety of changes, this flexibility is essential for preserving maximum performance.

The auto-encoder's multilayered design makes it easier to acquire complex characteristics, which helps the DMAE-DNN identify small defects in metallic surfaces. Furthermore, strengthening the model over noise and disturbances is the deep neural network's robustness, which ensures accurate flaw discovery even in difficult operating conditions.

The DMAE-DNN is a complicated automated metallic surface fault detection solution that combines the benefits of robustness, multi-layered extraction of features and dynamic flexibility. This advancement in technology has great potential for using areas where fault detection accuracy and efficiency are critical for maintaining the structure's strength and security. Algorithm 1 displays the pseudocode for a Dynamic multi-layered auto encoder with a robust deep neural network.

Algorithm 1: Pseudocode for DMAE-DNN

```
import numpy as np
import tensorflow as tf
input_size = ...
encoding_dim = ...
hidden_layers = [...]
output_size = ...
def autoencoder_model():
    encoder_input = tf.keras.Input(shape = (input_size,))
    encoded = encoder_input
    for layer_size in hidden_layers:
        encoded = tf.keras.layers.Dense(layer_size, activation = 'relu')(encoded)
    encoder_output = tf.keras.layers.Dense(encoding_dim, activation = 'relu')(encoded)
    decoder_input = tf.keras.layers.Input(shape = (encoding_dim,))
    decoded = decoder_input
    for layer_size in reversed(hidden_layers):
        decoded = tf.keras.layers.Dense(layer_size, activation = 'relu')(decoded)
    decoder_output = tf.keras.layers.Dense(input_size, activation = 'sigmoid')(decoded)
    encoder_model = tf.keras.Model(encoder_input, encoder_output)
    autoencoder_model = tf.keras.Model(encoder_input, decoder_output)
    return autoencoder_model, encoder_model
def dnn_model(encoding_dim):
    model = tf.keras.Sequential()
    model.add(tf.keras.layers.InputLayer(input_shape = (encoding_dim,)))
    for layer_size in hidden_layers:
        model.add(tf.keras.layers.Dense(layer_size, activation = 'relu'))
    model.add(tf.keras.layers.Dense(output_size, activation = 'softmax'))
    return model
autoencoder, encoder = autoencoder_model()
dnn = dnn_model(encoding_dim)
autoencoder.compile(optimizer = 'adam', loss = 'binary_crossentropy')
dnn.compile(optimizer = 'adam', loss = 'categorical_crossentropy', metrics = ['accuracy'])
autoencoder.fit(train_data, train_data, epochs = num_epochs, batch_size = batch_size, validation_data = (val_data, val_data))
encoded_data_train = encoder.predict(train_data)
encoded_data_val = encoder.predict(val_data)
dnn.fit(encoded_data_train, train_labels, epochs = num_epochs, batch_size = batch_size, validation_data = (encoded_data_val, val_labels))
evaluation_result = dnn.evaluate(encoded_data_test, test_labels)
print("EvaluationResult: " evaluation_result)
```

3. RESULTS

3.1 Data sample

The data of metallic flaws images was collected from a flat metal element manufactured utilizing an industrial microscope. An experienced examiner evaluates each component in advance, marking the faulty area and its type on each label. The number of defective images in a real industrial manufacturing line is very small. Additionally, obtaining and labelling defective images requires a significant financial investment and manual effort. Finally, we gathered 60 images for this flaw data, 40 of which were chosen at random for "training sets" and the rest of the images as testing sets. The categorization dataset comprised 464 images showing damage patches, scratches, dust, wrinkles and deformation. 60% of these images were employed for training and 40% were to be evaluated for testing in the categorization assignment.

The inspection experiment system was created with Python 3.11, with Tensor Flow serving as the deep learning computational platform. The acquired findings were derived from a server that includes an Intel Core i5 CPU and an NVIDIA GTX-1080ti GPU, which possesses 8 GB of video RAM. In this study, we evaluate the efficacy of the proposed methodology in comparison to the existing Logistic Regression (LR) (Peng et al., 2019) and "Support Vector Machine (SVM)" (Peng et al., 2019) approaches by assessing the metrics of Precision (%), F1-score (%) and Recall (%).

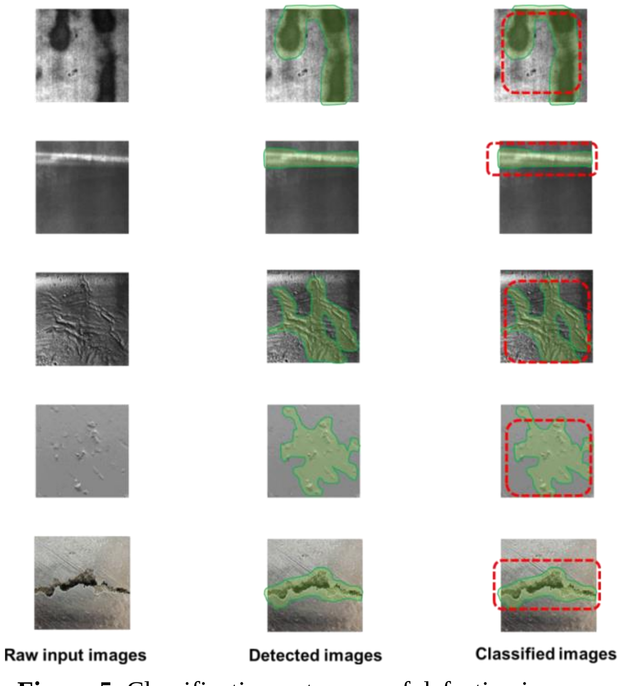

Figure 5. Classification outcomes of defective images

Figure 5 depicts the detection results, which are shown in green for several complex samples. The robust deep neural network approach has good detecting results for the majority of difficulties. It is possible to neglect scratches and fails to discover a fine defective area. The suggested dynamic multi-layered auto encoder approach differentiates between flaws and backgrounds in a simple way. It demonstrates strong capability in a variety of difficult circumstances.

The comprehensive categorization results for the three approaches are displayed in Figure 6. Traditional machine-learning approaches involve the creation of features to train the model. However, DMAE+DNN have accomplished training that incorporates the entire process, starting from feature learning and concluding with the exact output of the categorization outcomes. As displayed in Figure 6, the conventional approach makes it hard to distinguish among the three kinds of dust, wrinkles and patches. This could be the result of their surface and gradient data that is similar to one another that it can be hard to differentiate them. However, our approach is more effective at differentiating between wrinkles and patches, with a wrinkles classification rate of over 84%. Our proposed DMAE+DNN method has higher efficiency in detecting the various defects in the metal surface.

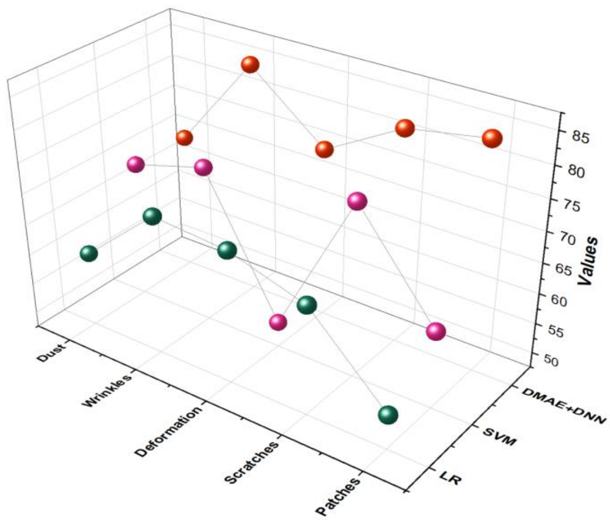

Figure 6. Detailed classification outcomes of three approaches

Precision is the accuracy with which true positives are identified from reported defects. The metric quantifies the proportion of correctly recognized defects to the overall number of reported defects. The proposed DMAE+DNN model achieves a precision rate of 86%, outperforming the existing methods, such as LR and SVM, which have precision rates of 75% and 72.2%, respectively, as shown in Figure 7 and Table 2. Achieving a high degree of precision is important for ensuring constant and effective identification of flaws while minimizing the possibility of false positives as well as enhancing the overall effectiveness of inspections.

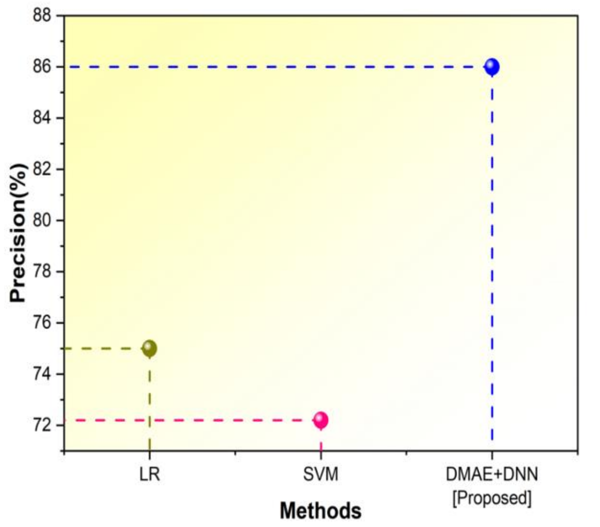

Figure 7. Outcomes of precision

Table 2. Result of precision

Methods	Precision (%)
LR	75
SVM	72.2
DMAE+DNN [Proposed]	86

Recall measures the percentage of actual flaws in the system accurately identified in relation to the total number of flaws. This calculation involves dividing the number of true positive results by the sum of true positives and false negatives. Table 3 and Figure 8 show the result of the recall. The effectiveness of our proposed DMAE+DNN is demonstrated by its 75% recall ratio, which is higher than the recall ratios of the two existing approaches, LR and SVM, which are 42.9% and 50%, respectively.

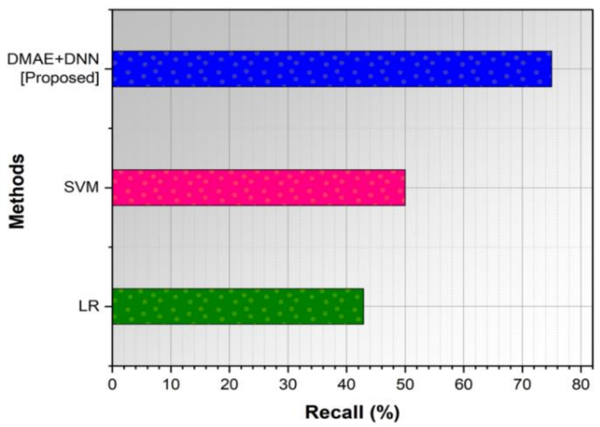

Figure 8. Outcomes of recall

Table 3. Output of recall

Methods	Recall (%)
LR	42.9
SVM	50
DMAE+DNN [Proposed]	75

The F1 score is a significant metric for evaluating the effectiveness of automated systems used in defect inspection on metal surfaces. A balanced score is provided by the combination of recall and precision in the evaluation, which measures a model's ability to identify and categorize issues while minimizing the number of “false positives” and “false negatives.”This presents an accurate assessment of the system's efficiency. The F1-score of the LR and SVM techniques were 87.5% and 58.3%, respectively. Meanwhile, the proposed DMAE+DNN methodology achieved an F1-score of 89.6%, demonstrating its superior effectiveness, which is displayed in Table 4 and Figure 9.

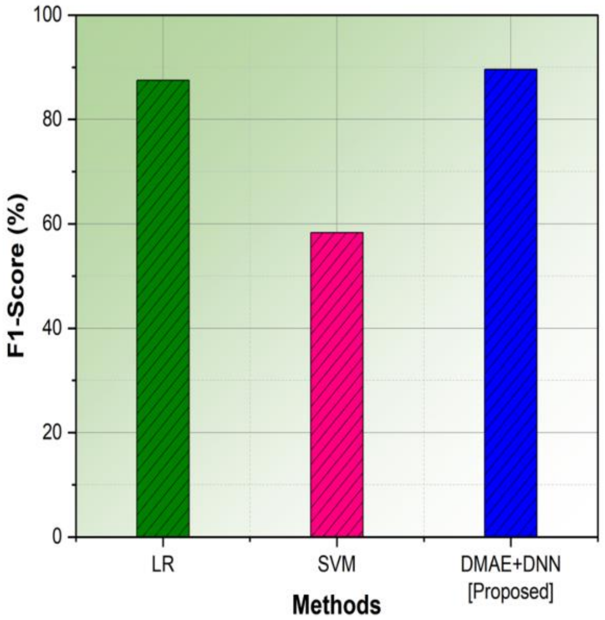

Figure 9. Outcomes of F1-score

Table 4. Result of F1-score

Methods	F1-Score (%)
LR	87.5
SVM	58.3
DMAE+DNN [Proposed]	89.6

4. CONCLUSION

Automated metallic surface flaw evaluation makes use of modern technology to inspect metal surfaces thoroughly for flaws, assuring precision as well as effectiveness in flaw detection. This procedure reduces human error while improving production quality control. In this study, we proposed a method for analyzing faults in metallic surfaces that combines a dynamic multi-layered auto-encoder with a robust deep neural network (DMAE+DNN). The performance is evaluated in terms of recall, precision and F1-score. Our suggested method outperforms other methods in terms of recall (75%), precision (86%) and F1-score (89.6%). Automated fault detection system integration might be a difficult task to implement into current manufacturing procedures. Furthermore, it could be necessary to continuously track and modify the system to sustain its efficiency over time, particularly in dynamic circumstances. The challenges of the future reside in overcoming the integration of automated fault detection into manufacturing procedures, which will require constant attention to all aspects and upgrades to maintain optimal performance in constantly shifting environments that reflect the changing industrial environments and modern technologies.

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