Journal of Electrical and Electronics Engineering (IOSR-JEEE)
e-ISSN: 2278-1676, p-ISSN: 2320-3331, Volume 20, Issue 4 Ser. 1 (July. – August. 2025), PP 28-33
www.iosrjournals.org

Performance Comparison of Activation Functions in CNN-Based Model for Metal Surface Defect Detection

Israt Jahan
(Department of Electrical and Electronic Engineering, Noakhali Science and Technology University, Bangladesh)

Abstract:
Metal surface defect detection plays a critical role in automatic quality control systems for metal manufacturing industries. This study proposes an automated defect classification approach using a Sequential Neural Network model. The performance of five activation functions, such as Rectified Linear Unit (ReLU), Leaky ReLU (LReLU), Swish, Mish, and Exponential Linear Squashing (ELiSH), was evaluated based on classification accuracy, precision, recall, loss, confusion matrices, and learning curve behavior. The publicly available NEU Metal Surface Defect Detection dataset from Kaggle was used, which contains 1,800 images across six defect classes: crazing, inclusion, patches, pitted surface, rolled-in scale, and scratches. The model was trained for 25 epochs, with data augmentation techniques applied to enhance generalization during training. Experimental results show that Mish outperforms the other activation functions across all evaluation metrics, achieving training accuracy, precision, and recall of 99.82%, along with the lowest loss value of 0.0096. While Swish and ELiSH demonstrate comparable performance, their fluctuating learning curves and higher loss values indicate reduced stability. These findings highlight the importance of selecting appropriate activation functions when designing intelligent systems for industrial visual inspection tasks.

Keywords: *Activation function, convolutional neural network, defect detection, metal surface, Mish.*

Date of Submission: 21-07-2025 Date of Acceptance: 31-07-2025

I. Introduction

Defect inspection of metal surfaces is very crucial to ensure the proper quality of metal for industrial manufacturing. Metal surfaces can have various types of defects, such as scratches, inclusions, patches, and some other kinds of defects too. These defects can impact product performance as well as customer satisfaction. Previously, defect inspections were done either manually or with the help of traditional machines [1]. Both methods suffer from complexity and poor adaptability. On the other hand, Convolutional Neural Networks-based automatic surface detection systems have made significant improvements using their feature extraction capabilities from image datasets [2]. Identifying different types of defect datasets without error is very important for manufacturing in industries.

Five well-known and popular activation functions named Rectified Linear Unit (ReLU) [3], Leaky ReLU (LReLU) [4], Swish [5], Mish [6], and ELiSH [7] have been used in the CNN model to classify metal surface defects. The NEU Metal Surface Defect database [8,9] from Kaggle, which has six types of defect classes, has been used for defect classification. A sequential CNN model with these activation functions has been trained with the above-mentioned dataset.

The aim of this paper is to investigate different activation functions' performance in a CNN model to carefully classify the six different types of metal surface defects in the NEU Metal Surface Defect dataset and compare the performance, such as accuracy, loss, precision, and recall, identifying which activation function works better in this case. Overall, this paper aims to offer practical guidance to model designers and industrial engineers in choosing the most suitable activation functions for defect detection tasks.

In the rest of the paper, the methodology has been described in section 2, section 3 elaborates on dataset preparation, section 4 explains the results and discussions, and finally section 5 summarizes the conclusion.

II. Methodology

Convolutional Neural Network (CNN)

In this work, a sequential convolutional neural network [10] has been used, in which five two-dimensional hidden convolution layers are used and the activation functions used in these layers have been changed with ReLU, LReLU, Swish, Mish, and ELiSH. For different activation functions, the results have been obtained and compared. After each convolutional layer, two-dimensional max-pooling layers have been used. After all these layers, a dense layer with different activation functions for comparison, followed by a dropout layer and an output layer with SoftMax activation function, has been used. The network works as a multi-class classifier to classify six types of images.

Activation Functions

In any neural network, activation functions work as the heart of that network. It adds non-linearity to the model, which eventually helps the model to find out the hidden patterns within the data. Activation functions actually decide the model's capability to perform better in different datasets. Better performance of the model means better accuracy, better precision and recall, less loss, and less computational complexity, and finally classifies each class successfully.

In the literature, there are several promising activation functions already used in different models. ReLU is widely used and is the most popular activation function currently used. But in some cases, ReLU fails to impress due to the “dying ReLU” issue. For this reason, different comparatively new activation functions have come to light. LReLU is one of them, which completely solves the “dying ReLU” problem. But the value of α should be chosen wisely, otherwise it can show an exploding gradient problem in the negative region, and it is also a piecewise function like ReLU.

In contrast, Swish is a smooth, non-monotonic function proposed by researchers at Google. It has demonstrated superior performance over ReLU in deeper networks by maintaining small negative outputs. This facilitates better gradient flow and prevents early neuron deactivation. Mish is another smooth and non-monotonic activation function, which combines the benefits of Swish and improves regularization. It offers better generalization, stability, and convergence, especially in complex classification tasks. Exponential Linear Squashing (ELiSH) is a more recent activation function designed to combine the advantages of both ReLU-like and Sigmoid-like behaviors. Though it is a piecewise function, it offers smooth transitions between linear and non-linear regions, contributing to improved gradient propagation and classification accuracy in deep networks. A brief summary of these activation functions with their equations, advantages, and disadvantages, as well as their characteristic curves, is presented in Table 1 and Fig. 1, respectively.

Table 1. Summary of The Activation Functions Used in the CNN Model

Ref.	Activation Function	Equation	Advantages	Limitations
[11]	ReLU	$f(x) = \begin{cases} x \text{ } if \text{ } x > 0 \\ 0 \text{ } if \text{ } x \leq 0 \end{cases}$	• Simple, fast convergence • Reduces vanishing gradient	▪ Dying ReLU problem
[12]	LReLU	$f(x) = \begin{cases} x \text{ } if \text{ } x > 0 \\ \alpha x \text{ } if \text{ } x \leq 0 \end{cases}$	• Mitigation of dying ReLU problem	▪ Requires careful selection of α value
[13]	Swish	$f(x) = x.\sigma(x)$	• Smooth, non-monotonic • Improves accuracy over ReLU	▪ Slightly slower computation
[14]	Mish	$f(x) = x.\tanh(\ln(1+e^x))$	• Smooth, non-monotonic • Strong generalization	▪ Higher computational cost than ReLU
[15]	ELiSH	$f(x) = \begin{cases} \frac{x}{1+e^{-x}} + \tanh(x) \text{ } if \text{ } x \geq 0 \\ \frac{e^{-x}-1}{1+e^{-x}} \quad if \text{ } x < 0 \end{cases}$	• Smooth transitions • Enhanced gradient flow	▪ Slower ▪ Limited library support

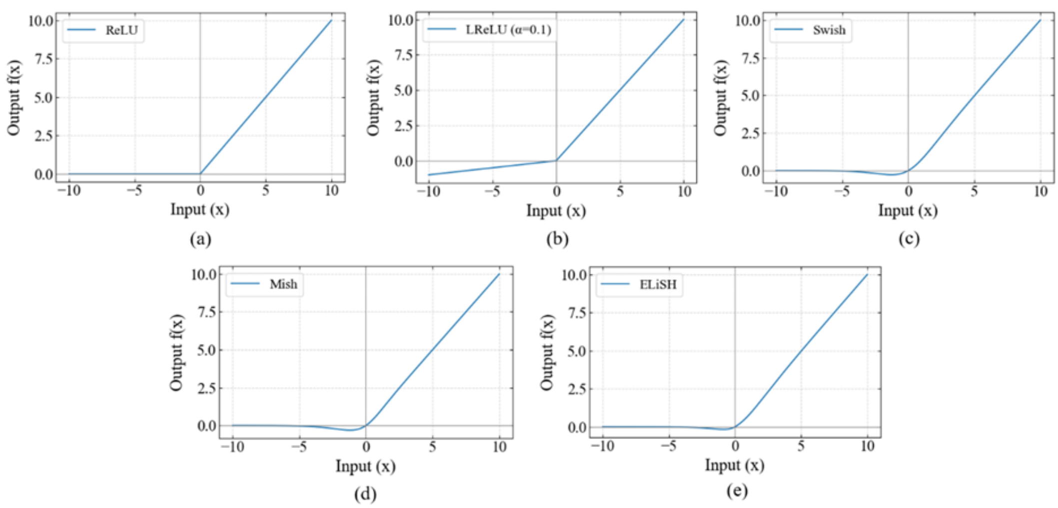


Fig. 1. Characteristics curves of the activation functions used in this study: (a) ReLU, (b) Leaky ReLU (LReLU), (c) Swish, (d) Mish, and (e) ELiSH.

III. Dataset Preparation

In this study, the publicly available *NEU Metal Surface Defect Database* from Kaggle is utilized to evaluate the performance of activation functions in the context of surface anomaly detection in metal industries [ref]. The *NEU Surface Defect Database*, developed by Northeastern University, contains grayscale images of common defects observed in hot-rolled steel strips. The dataset comprises a total of 1,800 grayscale images collected from a cold-rolling steel production line. Each image is of size 200 × 200 pixels and categorized into six distinct surface defect types, namely crazing, inclusion, patches, pitted surface, rolled-in scale, and scratches. Each class contains 300 images, ensuring a balanced class distribution suitable for multi-class classification tasks. These defects represent common anomalies encountered in real-world metal surface inspection systems and thus provide a practical benchmark for evaluating deep learning models in industrial settings. Sample images from each class are shown in Fig. 2.

For training and evaluation, all images were normalized and split into training, testing, and validation sets using a 92:4:4 ratio. Data augmentation techniques, including rotation, flipping, and zooming, were applied to increase dataset diversity and improve model generalization.

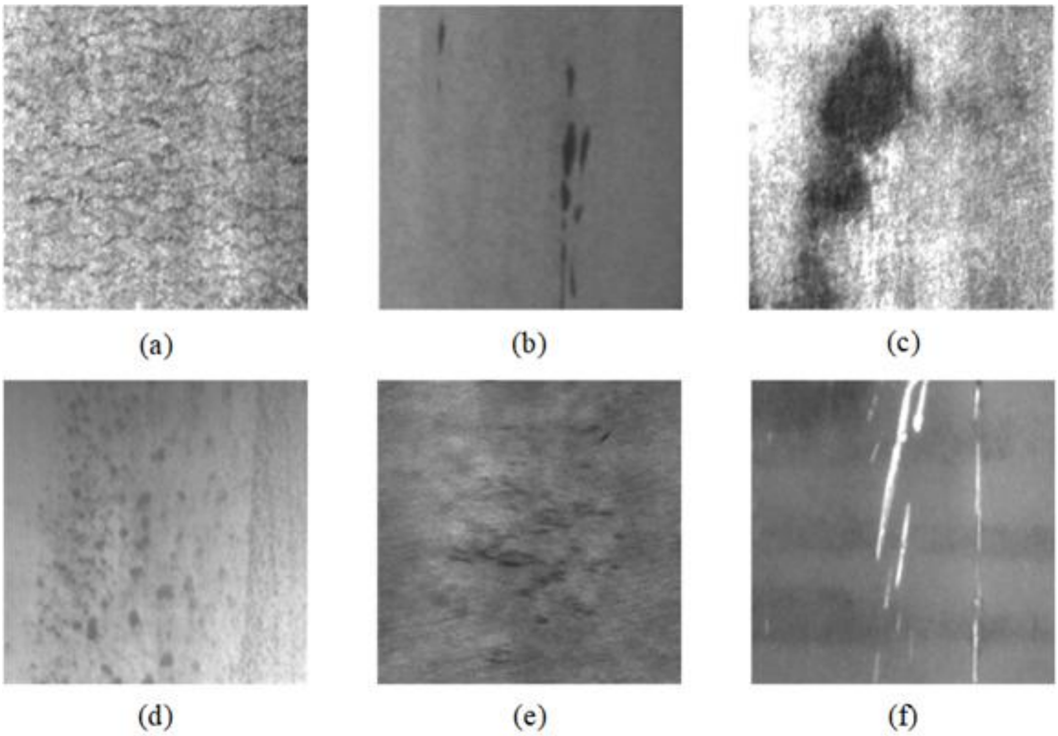


Fig. 2. Sample images from the *NEU Metal Surface Defect* dataset: (a) crazing, (b) inclusion, (c) patches, (d) pitted surface, (e) rolled-in scale, (f) scratches.

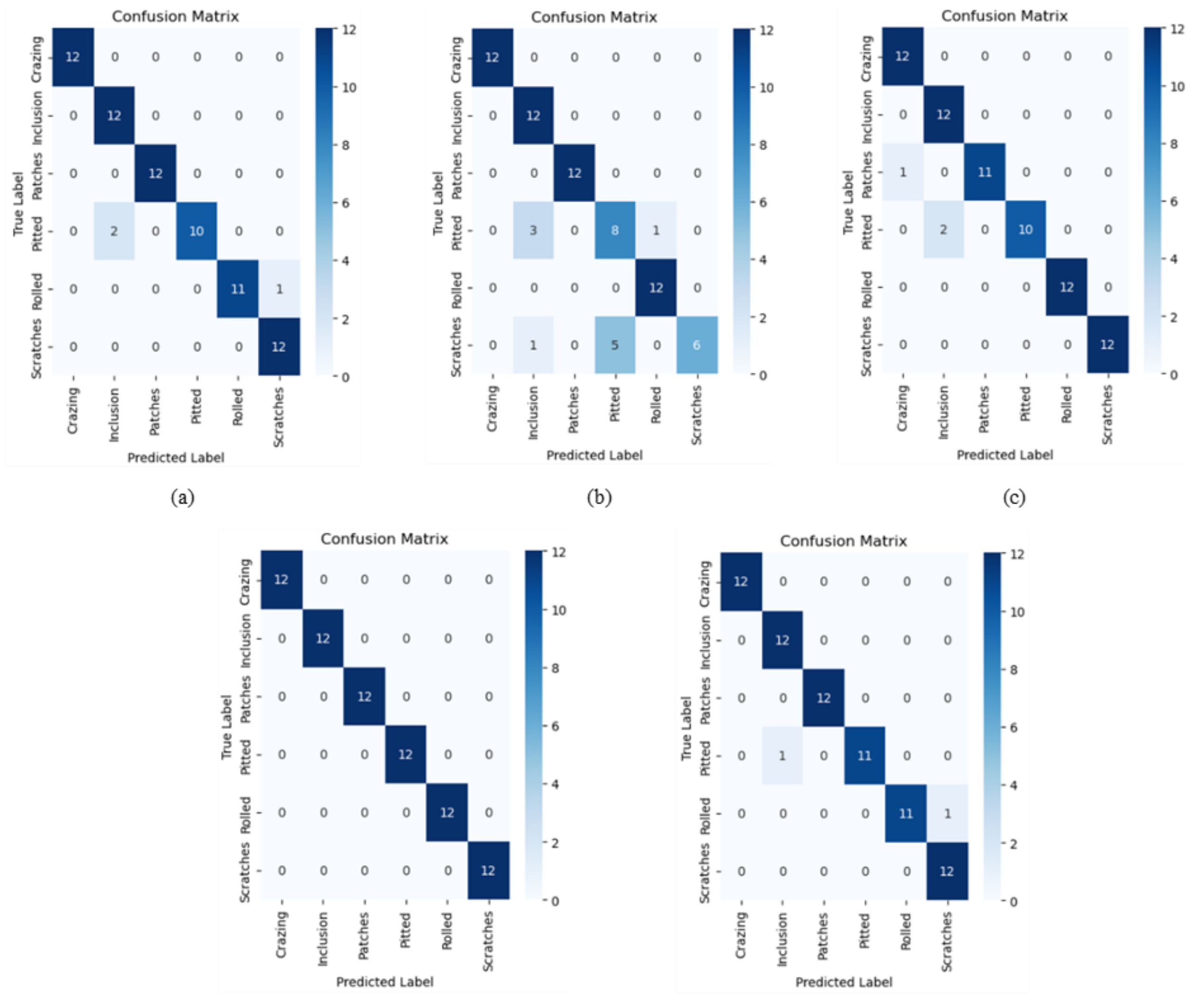
IV. Results And Discussions

To evaluate the effectiveness of different activation functions on an SNN model for metal surface defect classification, five activation functions, including ReLU, LReLU, Swish, Mish, and ELiSH, were tested. The model was trained for 25 epochs with a batch size of 32, and its performance was assessed in terms of accuracy, precision, recall, and loss. The results are summarized in Table 2.

Table 2. Performance of Activation Functions in Metal Surface Defect Classification

Activation Functions	Accuracy	Precision	Recall	Loss
ReLU	0.9861	0.9873	0.9861	0.0448
LReLU	0.9764	0.9805	0.9704	0.0866
Swish	0.9940	0.9946	0.9934	0.0237
Mish	**0.9982**	**0.9982**	**0.9982**	**0.0096**
ELiSH	0.9946	0.9946	0.9946	0.0227

In this scenario, Mish outperformed the others, achieving the highest training accuracy, precision, and recall of 99.82%, along with the lowest loss value of 0.0096. While Swish and ELiSH demonstrated comparable performance; however, their loss values, 0.0237 and 0.0227, respectively, were significantly higher than that of Mish, indicating reduced generalization.



(a) (b) (c) (d) (e)

Fig. 3. Confusion matrices for each activation function tested on the *NEU Metal Surface Defect* dataset: (a) ReLU, (b) LReLU, (c) Swish, (d) Mish, and (e) ELiSH.

To assess class-wise classification performance, the confusion matrices for the five activation functions are illustrated in Fig. 3. Mish perfectly classified all the test images, as indicated by zero values in all off-diagonal entries. In contrast, all the other activation functions misclassified at least one of the 12 test samples from the pitted surface class as inclusion. Among the remaining activation functions, ELiSH also demonstrated strong generalization performance, followed closely by Swish, which showed minor confusion. LReLU exhibited the weakest performance, with a significant number of misclassifications across multiple defect classes.

Finally, the training, validation, and loss curves are presented in Fig. 4 to evaluate the generalization capabilities of the tested activation functions in this application. Mish demonstrates the most stable and fastest convergence, as evident in Fig. 4(d).

While ELiSH and Swish also achieve strong performance metrics, their learning curves show some fluctuations, leaving Mish as the most suitable activation function under the current experimental setting. In contrast, although the learning curves of ReLU and LReLU eventually stabilize, their overall performance is less favorable, as discussed previously.

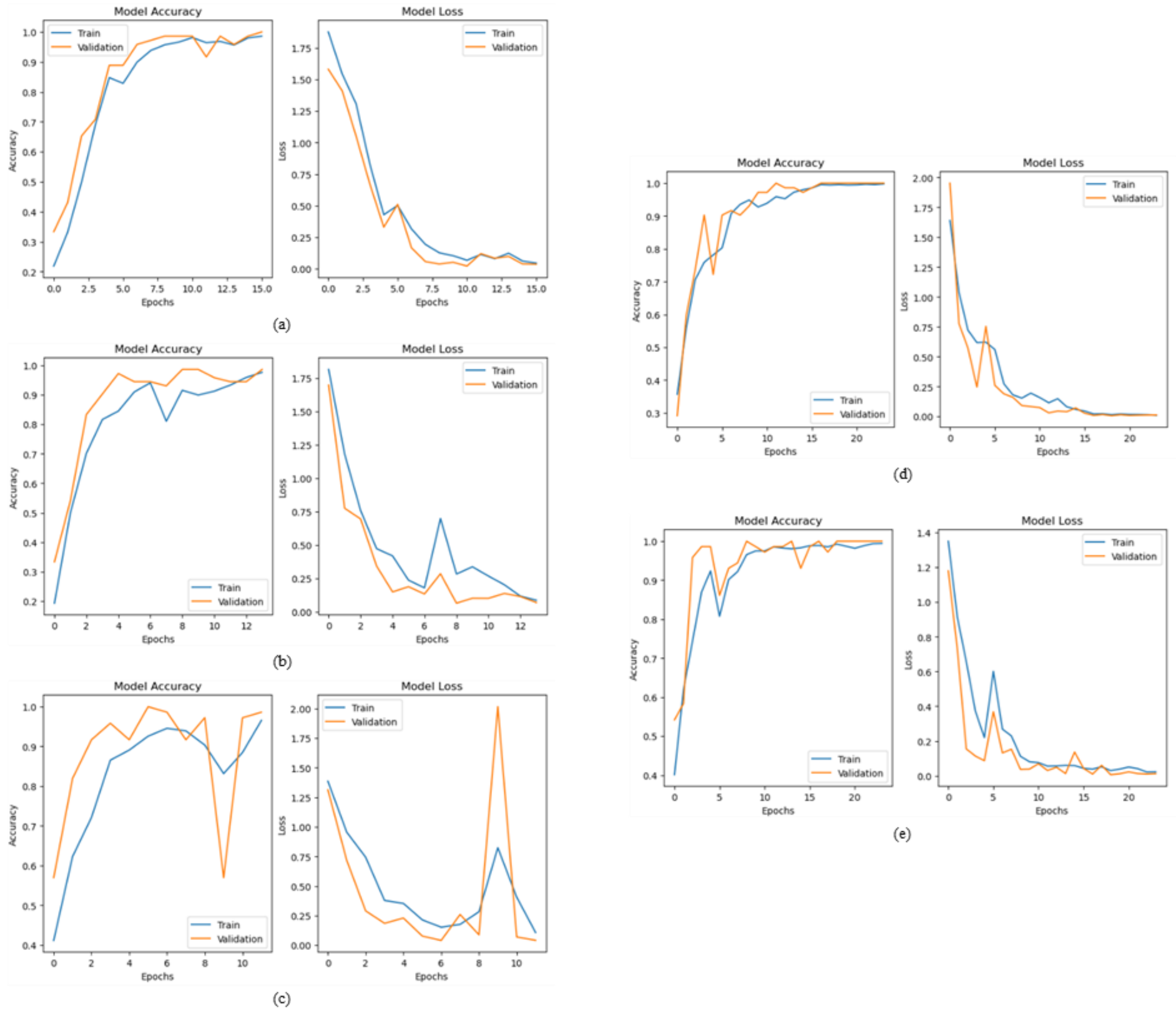


Fig. 4. Training and validation accuracy and loss curves for each activation function tested on the *NEU Metal Surface Defect* dataset: (a) ReLU, (b) LReLU, (c) Swish, (d) Mish, and (e) ELiSH.

V. Conclusion

This paper presents a comparative analysis of five activation functions, including ReLU, LReLU, Swish, Mish, and ELiSH, within an SNN framework for metal surface defect classification. The *NEU Metal Surface Defect* dataset from Kaggle was used to evaluate the effectiveness of these activation functions in detecting six common types of metal surface defects. Among the tested functions, Mish achieved superior results, with training accuracy, precision, and recall all reaching 99.82% and the lowest loss value of 0.0096, demonstrating both high predictive performance and strong generalization. While Swish and ELiSH showed comparable accuracy, their higher loss values and fluctuating learning curves suggested less training stability. In contrast, LReLU and ReLU exhibited more misclassifications, particularly in distinguishing challenging defect classes such as pitted surface and inclusion. Thus, Mish is identified as the most suitable activation function in this case. These findings emphasize the importance of selecting appropriate activation functions when designing deep learning models for industrial visual inspection systems, particularly in limited data scenarios.

References

[1] J. Jiang, C. Li, X. Zhang, J. Wang, And C. Liu, "Surface Defect Detection of High Precision Cylindrical Metal Parts Based on Machine Vision," In Proc. Intelligent Robotics and Applications (ICIRA), Lecture Notes in Computer Science, Vol. 13014, Pp. 810–820, Cham, Switzerland: Springer, 2021.

[2] Z. Li, X. Wei, M. Hassaballah, Y. Li, And X. Jiang, "A Deep Learning Model for Steel Surface Defect Detection," Complex & Intelligent Systems, Vol. 10, Pp. 885–897, 2024.

[3] V. Nair and G. E. Hinton, "Rectified Linear Units Improve Restricted Boltzmann Machines," In Proc. 27th Int. Conf. On Machine Learning (ICML), Haifa, Israel, 2010, Pp. 807–814.

[4] A. L. Maas, A. Y. Hannun, And A. Y. Ng, "Rectifier Nonlinearities Improve Neural Network Acoustic Models," In Proc. 30th Int. Conf. On Machine Learning (ICML), Vol. 28, 2013.

[5] P. Ramachandran, B. Zoph, And Q. V. Le, "Searching for Activation Functions," Arxiv Preprint Arxiv:1710.05941, 2017.

[6] D. Misra, "Mish: A Self Regularized Non-Monotonic Neural Activation Function," Arxiv Preprint Arxiv:1908.08681, 2019.

[7] A. Basirat And S. M. Roth, "The Quest for The Golden Activation Function," In Proc. IEEE International Conference on Machine Learning and Applications (ICMLA), Orlando, Fl, Usa, Dec. 2018, Pp. 93–100.
[8] Kaggle.Com. [Online]. Available: Https://Www.Kaggle.Com/Datasets/Paultimothymooney/Neu-Metal-Surface-Defects-Data.
[9] X. Song and Y. Yan, "Neu Surface Defect Database for Machine Vision Research.
[10] "Metal Surface 2," Kaggle.Com, 03-Apr-2025. [Online]. Available: Https://Www.Kaggle.Com/Code/Sarthakwadegaonkar/Metal-Surface-2.
[11] G. Klambauer, T. Unterthiner, A. Mayr, And S. Hochreiter, "Fast and Accurate Deep Network Learning by Exponential Linear Units (ELUs)," Neural Networks, Vol. 48, Pp. 1–10, 2015.
[12] T. Szandała, "Review and Comparison of Commonly Used Activation Functions for Deep Neural Networks," In Bio-Inspired Neurocomputing, Singapore: Springer Singapore, 2021, Pp. 203–224.
[13] M. Xu, P. Dai, And X. Huang, Is It Time to Swish? Comparing Deep Learning Activation Functions. 2019.
[14] "Activation Functions: Comparison of Trends in Practice and Research for Deep Learning. 2018.
[15] G. L. Wu, W. Pan, And S. Xu, "Comparison of Activation Function on Extreme Learning Machine: Swish, Elish, And Others," Aip Conference Proceedings, 2020.