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# Performance Analysis of Activation Functions for Marble Surface Anomaly Detection Using Deep CNNs

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***Abstract:***
*Surface anomaly detection is a key function in automatic quality control systems for marble industries that produce marble-like tile materials. This study proposes automated quality control in detecting marble tile surface defects using DenseNet-201, a deep convolutional neural network (CNN) model. The performance of various activation functions, such as Rectified Linear Unit (ReLU), Swish, Mish,* Gaussian Error Linear Unit *(GELU),* Activate or Not *(ACON-C), Meta-ACON, Snake,* Deep Interactive Click Extraction *(DICE), and Leaky ReLU (LReLU) was evaluated on publicly available Marble Surface Anomaly Detection dataset from Kaggle over 50 training epochs. This dataset comprises 55 color images of defective and non-defective classes, which were resized to 48×48 pixel sizes and augmented through standard image transformation methods in order to enhance generalization performance during the model training phase. Experimental results show that ACON-C and LReLU (with α value of 0.01) outperform others in terms of test accuracy of 75%, while the minimum test loss was achieved by LReLU (0.4771). On the other hand, DICE exhibited overfitting despite their strong training performance. These findings highlight the significance of proper activation function selection in designing CNN models for industrial visual inspection under limited data conditions.*

***Keywords:*** *Anomaly detection, CNN, deep learning, Leaky ReLU, smart tiles factory.*

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## I. Introduction

Perfection in the outer surface of marble and tile products is a critical factor in maintaining product quality and meeting industry standards. Traditionally, surface anomaly detection has been performed manually through visual inspection, which is labor-intensive, subject to variability, and impractical for high-volume production environments. Consequently, the demand for automated visual examination systems with the capability of accurately identifying surface defects such as cracks, scratches, and irregular textures.

Visual anomaly detection, very often referred to as anomaly detection in images, is a significant area of both theoretical and applied research [1]. In recent years, researchers have increasingly focused on vision-based defect detection in industrial applications using deep learning techniques, such as concrete surface crack detection [2] and steel surface defect detection [3]-[7]. Among various architectures, DenseNet-201 has emerged as a promising candidate for such tasks, owing to its effective feature reuse, improved gradient flow, and parameter efficiency [8]. Although the proper use of the network is extremely important, the activation function used in the layers of the network plays a very crucial role in achieving better performance.

To identify the most effective activation function for our specific scenario, we have considered nine activation functions including both traditional and recently proposed variants, to be applied to the final fully connected layers of DenseNet-201 architecture. These include Rectified Linear Unit (ReLU), Leaky ReLU (LReLU), Swish, Mish, Gaussian Error Linear Unit (GELU), Activate or Not (ACON-C), Meta-ACON, Snake, and Deep Interactive Click Extraction (DICE). Despite having a very simple mathematical equation, LReLU with α value of 0.01 has shown an outstanding performance in detecting the surface anomaly of marble tiles which can be used for industrial purposes. The simplicity of LReLU has helped it to overcome the overfitting problem in small-size datasets.

## II. Methodology

Deep Learning Model

In this work, the DenseNet-201 (Densely Connected Convolutional Network-201), a pre-trained image classification model with 201 layers has been used with different activation functions in the hidden layers. The DenseNet is special due to its feature reuse capability from any previous layers. This feature reuse capability of this network differs from conventional CNNs, where only a previous layer passes information to its immediate next layer. As an advantage of this capability, DenseNet can work very well when there is a limited number of training data available. In this study, DenseNet-201 is utilized as the backbone model for marble surface anomaly identification [9]. The final layer was modified for binary classification of tile quality, such as defective tiles and non-defective tiles, and various activation functions were applied to determine the most suitable one for industrial visual inspection applications.

Activation Functions

Activation functions are regarded as the heart of neural networks because they give the model non-linearity, which helps it recognize and extract intricate patterns in the data. Considering various characteristics such as accuracy, loss behavior, and computational complexity, a significant number of activation functions have been suggested in the literature. Each activation function comes with its own limitations. For instance, ReLU is struggling from the dying ReLU issue, where it provides zero output regardless of the input. In contrast, LReLU addresses this problem but lacks noise robustness.

The objective is to identify which functions provide superior generalization and robustness, particularly under limited data conditions typical of industrial visual inspection tasks. A brief overview of these activation functions and their corresponding characteristics curves is presented in Table 1 and Fig. 1.

Table 1. Brief descriptions of the activation functions used in this study.

| Ref. | Activation Function | Equation | Advantages | Limitations |
|---|---|---|---|---|
| [11] | ReLU | $f(x) = \begin{cases} x \; if \; x > 0 \\ 0 \; if \; x \le 0 \end{cases}$ | Simple, fast convergence, reduces vanishing gradient | Dying ReLU problem (neurons stuck at 0) |
| [12] | Swish | $f(x) = x.\sigma(x)$ | Smooth, non-monotonic, improves accuracy over ReLU | Slightly slower to compute |
| [13] | Mish | $f(x) = x.\tanh\,(\ln\,(1 + e^x))$ | Smooth, non-monotonic, strong generalization | More computational cost than ReLU |
| [14] | GELU | $f(x) = x.\Phi(x)$ | Probabilistic, used in BERT/ViT, strong performance | Harder to interpret; slower than ReLU |
| [15] | ACON-C | $f(x) = (p_1x - p_2x).\sigma(\beta(p_1x - p_2x))$ | Learns to activate or not, flexible | Requires custom layers and tuning |
| [15] | Meta-ACON | Same as ACON-C but with dynamic β via meta-network | Adaptive to input, strong state-of-the-art performance | Higher complexity, needs more training time |
| [16]-[17] | DICE | $f(x) = p(x).x + (1 - p(x)).\alpha x$, where $p = \sigma(BN(x))$ | Channel-wise adaptivity, good in segmentation | Needs batch norm, not plug-and-play |
| [18-19] | Snake | $f(x) = x + \frac{1}{\alpha}sin^2(\alpha x)$ | Great for textures and patterns (e.g., cracks) | Overfits if not regularized; sensitive to α |
| [20] | LReLU | $f(x) = \begin{cases} x \; if \; x > 0 \\ \alpha x \; if \; x \le 0 \end{cases}$ | Mitigates the dying ReLU problem | α should be chosen wisely |

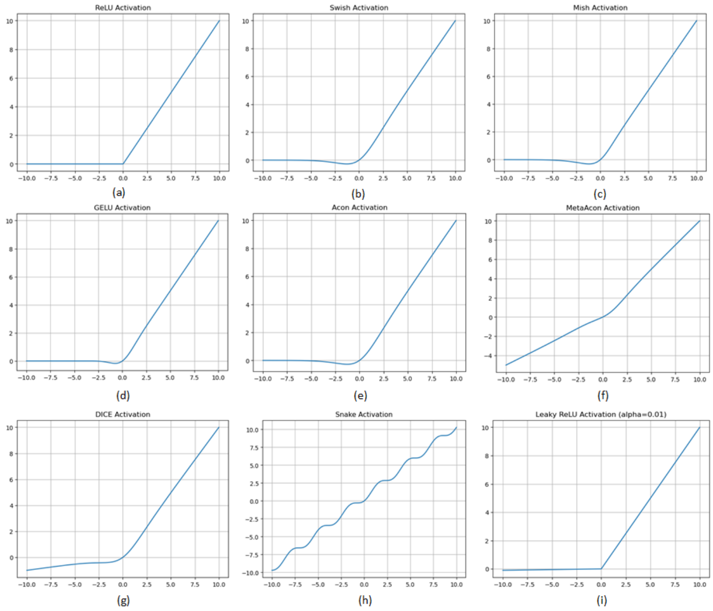


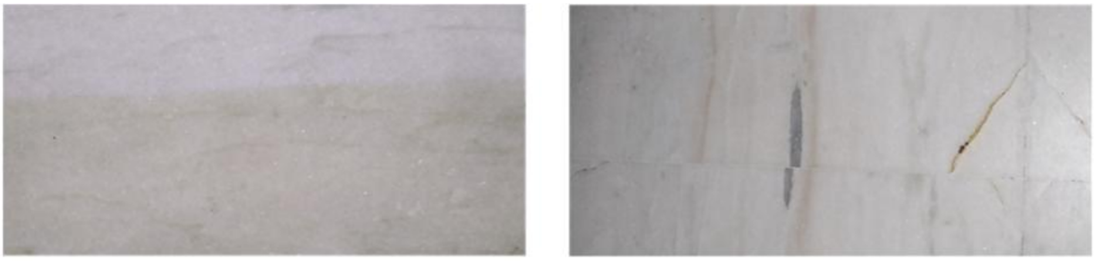

Fig. 1. Characteristics curves of the activation functions used in this study; (a) ReLU, (b) Swish, (c) Mish, (d) GELU, (e) ACON-C, (f) Meta-ACON, (g) DICE, (h) Snake, and (i) Leaky ReLU.

## III. Dataset Preparation

In this work, the publicly available *Marble Surface Anomaly Detection* dataset from Kaggle is utilized to evaluate the effectiveness of activation functions in the context of industrial visual inspection and surface anomaly detection [10]. This dataset contains 55 color images and serves as a real-world benchmark for binary surface quality classification of marble tiles. It consists of two classes, such as defective tiles and non-defective or good tiles. The defective class contains 20 images with apparent surface defects like lines, cracks, and other irregularities that make the marble's aesthetic or structural quality defective. The non-defective class contains 35 images of smooth, uniform, and flawless marble surface images.

A visual representation of sample images from each class is shown in Fig. 2. All images were resized to 48 × 48 pixels and then split into training and test datasets with an 80:20 data-splitting ratio.

During the model training phase, an image augmentation technique was utilized, which incorporated random rotation, zoom, shifting, and both horizontal and vertical flipping. All these augmentations were applied to improve the model's generalization capability and prevent overfitting with this small dataset.



(a) (b)

Fig. 2. Sample images from the *Marble Surface Anomaly Detection* dataset: (a) non-defective tile, (b) defective tile with visible surface irregularities.

## IV. Results And Discussion

To determine the effect of different activation functions on a DenseNet-201 based model's performance in tiles quality classification, nine activation functions were tested for comparison: ReLU, Swish, Mish, GELU, ACON-C, Meta-ACON, SNAKE, DICE, and LReLU. The batch size was set to 32 and the models were trained for 50 epochs and comparison was carried out in terms of both loss and accuracy for the training and test datasets. The experimental results are presented in Table 2.

Table 2. Performance of activation functions in marble surface anomaly classification.

| Activation Function | Loss | | Accuracy (%) | |
|---|---|---|---|---|
| | Training | Test | Training | Test |
| ReLU | 0.2606 | 0.6507 | 90.32 | 62.50 |
| Swish | 0.2897 | 0.8961 | 90.32 | 50.00 |
| Mish | 0.4018 | 0.9591 | 83.87 | 50.00 |
| GELU | 0.2791 | 0.9019 | 90.32 | 62.50 |
| ACON-C | 0.1837 | 0.6078 | 90.32 | **75.00** |
| Meta-ACON | 0.2794 | 0.9777 | 93.55 | 62.50 |
| Snake | 0.2188 | 0.7825 | 90.32 | 62.50 |
| DICE | **0.1699** | 1.4449 | 93.55 | 37.50 |
| LReLU | 0.1946 | **0.4771** | **96.77** | **75.00** |

Both accuracy and loss of training dataset and test dataset are considered as performance metrics to observe the generalization capability and avoid overfitting issues. For instance, DICE demonstrated the best performance in terms of training loss i.e., 0.1699 which is the lowest among all other activation functions. DICE also shares the 2$^{nd}$ place in terms of training accuracy with Meta-ACON and the training accuracy is 93.55%. However, in case of test accuracy and test loss, DICE fails miserably. It scores lowest in the case of test accuracy (32.50%) and highest in the case of test loss (1.4449). So, it failed to generalize and suffered from an overfitting problem.

Some other activation functions like GELU, Snake, and Meta-ACON had shown stable training performances and modest test accuracy value of 62.50%, implying an appropriate balance between generalization and model complexity. Swish and Mish, though extensively used in current neural networks, had poor performance in this task of 50.00% for test accuracy and comparatively high values of 0.8961 and 0.9591 for test losses, respectively.

Considering the balance between accuracy and loss, ACON-C and LReLU (with α value of 0.01) appear to be the most promising activation functions for industrial applications in this particular scenario of small-scale industrial inspection datasets. Both of the functions achieved the highest test accuracy of 75.00%. Considering the test loss, LReLU achieved the lowest loss of 0.4771, while ACON-C also showed competitive results with a lower test loss of 0.6078. From the above discussion, it can be concluded that LReLU is mostly efficient as well as mathematically less complex activation function for image anomaly detection especially for marble anomaly detection.

## V. Conclusion

In this paper, the performance of different activation functions in hidden layers of DenseNet-201 for detecting defects on marble tiles has been investigated. The dataset has limited standard data that is publicly available. In terms of test accuracy and test loss, LReLU (α=0.01) has outperformed other activation functions. Most of the other activation functions have poor performance in the test dataset due to overfitting problems in the training dataset. Thus, LReLU is identified as the best activation function in this case. The findings of this research mark the importance of choosing proper activation functions for industrial visual inspection tasks, particularly in limited data scenarios. In future work, we will investigate the impact of activation functions on a larger, custom dataset for varying types of marble surfaces.

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