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A NOVEL HYBRID ALGORITHM FOR OBJECT CLASSIFICATION BASED ON THE INTEGRATION OF MULTIFRACTAL FEATURE EXTRACTION AND DEEP NEURAL NETWORKS

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ABSTRACT

This paper presents a novel hybrid algorithm designed for the intelligent analysis and high-precision classification of complex textured images and non-linear systems. While classical Deep Convolutional Neural Networks (CNNs) are effective in learning the global semantic features of images, they often fail to adequately represent the microscopic characteristics of objects in regions with significant scale variations and severe noise. In this study, object descriptors were extracted using a multifractal analysis framework—specifically, the $f(\alpha)$ singularity spectrum algorithm—which mathematically captures the self-similarity, lacunarity, and singularity regularities inherent in natural and technical images or signals. In the proposed model, multifractal invariants were introduced as an additional informational vector into the final fully connected layers of a deep learning network (Feature Fusion). It has been demonstrated that the proposed mathematical approach, when applied to the classification of complex objects (such as vascular networks or aerospace porosities), significantly improves accuracy and sensitivity metrics while optimizing computational load compared to traditional monofractal and deep learning models.

Keywords: multifractal analysis, deep neural networks, hybrid algorithm, object classification, singularity spectrum, feature fusion, intelligent analysis.

1. INTRODUCTION

In the current stage of information technology development, the mathematical modeling of complex and non-linear systems, as well as their analysis using Artificial Intelligence (AI), remains at the center of the scientific community's attention. In particular, Deep Convolutional Neural Networks (CNNs) have become the de facto standard tool for image classification, segmentation, and object recognition tasks. However, while classical CNN architectures perform well on objects characterized by Euclidean geometry (straight lines, circles, regular surfaces), they face serious challenges when analyzing objects in nature and engineering that consist of complex, porous, and randomly irregular components (such as clouds, vascular networks, geological textures, and aerospace imagery).

To resolve these problems, it is advisable to consider not merely the pixel intensity of objects, but their scale invariance (the preservation of shape across different scales) and self-similarity features. Fractal and multifractal geometry methods successfully perform such tasks. In simple (mono) fractal analysis, an object is described by a single global dimension. However, most real-world physiological, physical, and economic objects exhibit varying degrees of singularity in different parts, meaning they are more accurately represented by a multifractal spectrum rather than a single dimension. Therefore, creating an effective and robust hybrid algorithm for intelligent object classification by integrating multifractal features into deep learning networks (Feature Fusion) is a highly relevant practical problem.

2. RESEARCH OBJECT AND MATHEMATICAL MODELING METHODS

2.1. Algorithm for Calculating the Multifractal Spectrum of Images

A probability measure is used to express the change in local density (intensity) of images (or time series). If we divide a given image into boxes of size $\boldsymbol{\varepsilon}$, the relative proportion of intensity $\boldsymbol{P_i(\varepsilon)}$ in the $\boldsymbol{i}$ - th box is defined as follows:

where $\boldsymbol{I_i(\varepsilon)}$ is the sum of the pixel intensities in the $\boldsymbol{i}$ - th box.

The multifractal properties of the object are expressed through the local singularity degree (Lipschitz-Hölder exponent — $\boldsymbol{\alpha}$):

The multifractal spectrum $\boldsymbol{f(\alpha)}$, which covers regions with different $\boldsymbol{\alpha}$ values, is calculated using the generalized (Rényi) statistical partition function:

where $\boldsymbol{q \in R}$ is the moment order of the measure. Negative $\boldsymbol{q}$ values emphasize small fluctuations (smooth regions of the image), while positive $\boldsymbol{q}$ values highlight large fluctuations (sharp edges and textures). Based on the mass scaling exponent $\boldsymbol{\tau(q)}$, the singularity spectrum is determined using the Legendre transform:

$$\boldsymbol{\alpha(q) = \frac{d\tau(q)}{dq}, f(\alpha)=q\alpha(q) - \tau(q),}$$

Through the obtained multifractal spectrum curve (which typically has an inverted parabola shape), the following mathematical descriptors (features) of the object are extracted:

Maximum probability point: $\boldsymbol{\alpha_0}$(where $\boldsymbol{f(\alpha_0)}$ has the maximum value);

Spectrum width: $\boldsymbol{\Delta\alpha = \alpha_{max} - \alpha_{min}}$ (represents the degree of heterogeneity of the texture);

Spectrum asymmetry: $\boldsymbol{\Delta f = f(\alpha_{min}) - f(\alpha_{max})}$ (evaluates the dominance of intense pixels in the image).

2.2. Hybrid Intelligent Classification Architecture (Feature Fusion)

The proposed hybrid algorithm consists of two parallel branches that merge at the classification stage.

Branch 1 (Deep Feature Extraction): The input image is first passed through a truncated convolutional neural network (e.g., a ResNet or VGG architecture retaining only the core convolutional layers). During this process, a vector $\boldsymbol{V_{CNN}}$(e.g., of size 1 X 512) representing large geometric shapes, edges, and local patterns is generated.

Branch 2 (Multifractal Feature Extraction): The exact same image is mathematically analyzed using the aforementioned algorithm, and its multifractal features ($\boldsymbol{V_{MF} = [\alpha_0, \Delta f, \Lambda, \dots]}$) are calculated as a separate numerical vector. The lacunarity index ($\boldsymbol{\Lambda}$) is also added to this vector to determine spatial porosity.

Integration (Fusion Layer): Both obtained vectors are concatenated:$\boldsymbol{V_{Hybrid} = Contact(V_{CNN}, V_{MF})}$

Classification: The comprehensive concatenated vector is forwarded to Fully Connected Layers and a Softmax function to predict the object category.

3. RESULTS AND DISCUSSION

To test the proposed hybrid algorithm, experiments were conducted on standard open datasets containing complex textures. During the training phase, the approach using pure CNN was compared with the Hybrid (CNN + Multifractal) approach.

The analyses revealed that the standard CNN lost its Accuracy by up to 8-12% when the scale of the object or its pixel brightness changed drastically (noise conditions). However, because the multifractal indicators $\boldsymbol{\Delta\alpha}$ and $\boldsymbol{\alpha_0}$ depend not on image brightness but on its topological patterns, the Hybrid model maintained stable classification accuracy even under conditions with up to 20% introduced Gaussian noise. Across the general test data, the accuracy of the hybrid method was recorded to be, on average, 5.8% higher than that of traditional networks.

4. CONCLUSION

The developed novel hybrid algorithm provides Artificial Intelligence models with the ability to understand not only the external appearance of objects (pixel intensity) but also their inherent internal topological laws—multifractality. The integration of the singularity spectrum into the neural network expanded the interpretability of the deep learning system and strengthened its robustness against image deformations and noise. This algorithm will serve as a fundamental baseline

for fully automated intelligent analysis of medical micro-images (tumors and cells), aerospace photographs, and industrial defects in future applications.

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