

	(логарифми, корені) за наявності викидів	PCA, L1/L2 регуляризація	коефіцієнтів, методи ресемплінгу	coding, ordinal encoding
$D_3$	Пакет <i>stats</i> з функцією <i>glm()</i> у R, пакет <i>caret</i>			
$D_4$	Мінімальні	Можлива втрата інформативності	Можлива втрата інформативності	Неправильне кодування може знизити точність

#### Список використаної літератури

1. Ільїна О.П., Скибик С.Я. Моделювання ресурсного індикатору безпеки інтересів розподіленої системи організаційного управління з використанням класифікаційних методів машинного навчання // *Інформаційні технології і автоматизація – 2024*: матеріали XVII міжнародної науково-практичної конференції (Одеса, 31 жовтня – 1 листопада 2024 р.). – Одеса: Видавництво ОНТУ, 2024. – С. 69–72. – 847 с.
2. Bishop, C.M. (2006). *Pattern Recognition and Machine Learning*. New York: Springer.
3. Aggarwal, C.C. (2015). *Data Mining: The Textbook*. Springer.
4. James, G., Witten, D., Hastie, T., & Tibshirani, R. (2013). *An Introduction to Statistical Learning: with Applications in R*. Springer.

### OPTIMIZING SKIN IMAGE SEGMENTATION WITH FOURIER AND GRAPH-BASED METHODS

**Кіншаков Е.В., Парфененко Ю.В.** / Kinshakov E.V., Parfenenko Yu., V.  
 Сумський державний університет / Sumy State University  
 40007, Суми, вул. Харківська, 116,  
 E-mail: edikkinshakov@gmail.com, yuliya\_p@cs.sumdu.edu.ua

This paper introduces advanced methods for skin disease image segmentation using the Dermnet dataset, one of the largest resources in dermatology. Traditional approaches like Watershed and thresholding often fail due to the complex textures, color variations, and noise present in skin images. To address these challenges, novel techniques were proposed. First, the Fourier transform reduces high-frequency noise, preparing images for segmentation. Then, min-cut/max-flow graph algorithms minimize energy functions, enabling precise separation of pathological and healthy areas. Additionally, a piecewise smooth approximation improves boundary detection, refining segmentation results. Experiments demonstrated a 15% accuracy improvement over traditional methods. Processing time was also significantly reduced, enhancing the reliability and efficiency of automated diagnostic systems.

**Keywords:** segmentation, machine learning, image processing, skin diseases, Fourier transform, graph algorithms, computational optimization, piecewise approximation.

**Introduction and Problem Statement.** Image segmentation for medical diagnostics, particularly for skin diseases, poses challenges due to the complex textures, uneven boundaries, and noise in affected areas. The Dermnet dataset, a rich resource for research, highlights the limitations of traditional methods like thresholding and Watershed, which struggle with accuracy. Key challenges include distinguishing healthy and pathological areas, uneven illumination, and texture noise.

To address these issues, advanced methods have been proposed: Fourier transforms to reduce noise, graph algorithms for precise boundary segmentation, and piecewise smooth approximation for improved detection of pathological areas. This integrated approach enhances accuracy and minimizes false positives, offering a significant improvement over traditional algorithms.

**Problem solution and Results.** The first step in segmentation is preprocessing to remove noise and artifacts affecting accuracy. High-frequency noise from uneven illumination, glare, and skin texture is addressed using a Fourier transform, which filters out unwanted components in frequency space. Formally, this can be written as:

$$(1) \quad F(u, v) = \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} f(x, y) e^{-2\pi i \left( \frac{ux}{M} + \frac{vy}{N} \right)},$$

where  $f(x, y)$  is the intensity of a pixel in an image;  $M$  and  $N$  image dimensions;  $F(u, v)$  frequency domain result. After the transformation, we can apply a low-pass filter to remove noise, leaving only the important low-frequency components that are responsible for the main structural elements of the image. The image is then restored to its spatial representation through an inverse Fourier transform [2].

Noise was reduced by 12%, removing fine textures that could cause false positives. Min-cut/max-flow graph algorithms, modeling pixels as vertices and edges based on color and texture, significantly improved segmentation accuracy between healthy and affected areas [4]. A piecewise smooth approximation was used to improve boundary detection, enhancing contrast and reducing artifacts. Formally, the pixel intensity function is modeled as a piecewise smooth function:

$$(2) \quad S(x) = \sum_{i=1}^k \frac{(x-x_i)^2}{h_i^2},$$

where  $x_i$  control points corresponding to certain intensities in different parts of the image;  $h_i$  and the boundaries of the approximation region around the control points. This method handles texture variations in conditions like psoriasis, where boundaries are unclear. GPU-based parallel processing cuts execution time by 25%, enabling real-time diagnostics. Experiments on the Dermnet dataset showed 15% higher accuracy, 12% better completeness, and 10% fewer false positives, with segmentation time reduced to 1.5 seconds per image.

In **Fig.1** the segmented image with an overlay is visualized, where the pathological areas are overlaid in color onto the original image, allowing for a clearer comparison of the segmentation results with the actual skin condition.



Figure 1. Visualized segmented image with an overlay

## CONCLUSIONS

This paper introduces a new method for segmenting skin disease images from the Dermnet dataset, combining Fourier transform, graph algorithms, and piecewise smooth approximation. The approach outperforms traditional methods by reducing noise, enhancing pathological detection, and refining blurred boundaries. The method improves accuracy, reduces false positives, and enables real-time application through parallel processing. Future work includes developing automated diagnostic systems, training on larger datasets, and integrating pre-trained neural networks for better adaptability and accuracy.

## REFERENCES

- [1] C. B. Williams and D. J. Hughes, "Image preprocessing methods for noise reduction in medical imaging," *J. Med. Imaging*, vol. 38, no. 4, pp. 800-814, Apr. 2018.
- [2] A. P. Adams and S. J. Hartmann, "Removing high-frequency noise from medical images using Fourier transforms," *IEEE Trans. Med. Imaging*, vol. 37, no. 3, pp. 500-510, Mar. 2019.
- [3] H. R. Zhang and Q. M. Lee, "Fourier transform applications in image processing," *Signal Process.*, vol. 95, pp. 123-134, Jul. 2021.
- [4] L. J. Grant and M. L. Chen, "Noise reduction techniques for medical image segmentation," *Pattern Recognit. Lett.*, vol. 45, pp. 45-53, May 2020.

## КЕРОВАНІ ОБЕРНЕНІ ЗАДАЧІ / GUIDED INVERSE PROBLEMS

Іванюк А.О., Кравчук О.М., Крюкова Г.В. / Ivaniuk A., Kravchuk O., Kriukova G.

Національний університет "Києво-Могилянська Академія" / National University of Kyiv-Mohyla Academy

04655, Київ, вул. Григорія Сковороди, 2, факультет інформатики, кафедра математики

E-mail: a.ivaniuk@ukma.edu.ua, o.kravchuk@ukma.edu.ua, kriukovagv@ukma.edu.ua

The given work proposes a novel approach for solving inverse problems in machine learning leveraging Physics-Guided Neural Networks (PGNNs). Our method incorporates domain knowledge through an additional inverse problem, leading to significant improvements in model performance and accuracy. In this case, we focus on sentiment analysis to enhance text-to-speech generation. This integration of knowledge within the neural network architecture leads to a more interpretable and accurate model.

We validate our approach using text-to-speech synthesis on the EmoV-DB dataset, which contains multi-speaker recordings with various emotions. Our model significantly outperforms traditional generative techniques on this benchmark. By evaluating the model's strengths and weaknesses, we aim to glean valuable insights that can guide the development of future emotionally intelligent speech synthesis technologies. This analysis contributes to a broader understanding of latent diffusion's applicability and potential in diverse generative tasks. This demonstrates the effectiveness of our method as a scalable and efficient solution for tackling modern inverse problems in machine learning.

This work proposes a novel two-step domain-knowledge-guided approach to estimate output of the model ( $X$ ) from input data ( $Y$ ). We consider intrinsic quality attributes  $\beta$  that are inherently linked to the final output ( $X$ ).

The first step ( $X \rightarrow \beta'$ ) involves a domain-knowledge-guided inverse problem. This approach utilizes established domain knowledge and principles to transform input data ( $X$ ) into a lower-dimensional representation ( $\beta'$ ) capturing the essential quality attributes of the produce. This transformation is achieved without direct supervision from output dataset ( $Y$ ), relying solely on the inherent information within the input data ( $X$ ) and domain knowledge given by additional inverse problem. This process aims to extract the essence embedded within the data and solution of additional problem, and distill the information into quantifiable parameters  $\beta'$  that reflect the underlying quality attributes  $\beta$ .

The second step follows feature extraction, the estimated quality attributes ( $\beta'$ ) are used to predict the final output ( $X$ ) through a predictive model. This phase can employ various