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Publications based on thesis work

1. **Journal**

    - **Mahanta, D.**, Hazarika, D., and Nath, V. K. Local Bit-Plane Domain 3D Oriented Arbitrary and Circular Shaped Scanning Patterns for Bio-Medical Image Retrieval. **Journal of Image and Graphics**, 11(2), 2023. (Scopus)
    - **Mahanta, D.**, Hazarika, D., and Nath, V. K. Automated Diagnosis of COVID-19 Using Synthetic Chest X-Ray Images from Generative Adversarial Networks and Blend of Inception-v3 and Vgg-19 Features. **SN Computer Science**, 4(5), 558, 2023. (Scopus)
    - **Mahanta, D.**, Hazarika, D., and Nath, V. K. Hybrid deep features computed from spatial images and bit plane-based pattern maps for the classification of chest X-ray images **Journal of Radiation Research and Applied Sciences**, 17(3), 101024, 2024. (SCIE)
    - **Mahanta, D.**, Hazarika, D., and Nath, V. K. Classification of skin lesions utilizing DarkNet-53, ResNet-50, MobileNet-v2 models and their modified forms with CycleGAN generated synthetic images. (**Manuscript under preparation**)

2. **Conference**

    - **Mahanta, D.**, Hazarika, D., and Nath, V. K. Biomedical Image Retrieval using Muti-Scale Local Bit-plane Arbitrary Shaped Patterns. **National Conference on Communications (NCC)**, (pp. 1-6), 2021. IEEE, IIT Kanpur.