# Research Publications

1. **Histopathological Image-Based Classification of Lung and Colon Cancer Using Deep Learning Architectures with Preprocessing Enhancements** [1]

   This study addresses the pressing need for automated histopathological image analysis in lung and colon cancer diagnostics. Manual pathology is often subjective and time-consuming, motivating the use of deep learning (DL) to achieve reproducibility and precision. Leveraging the LC25000 dataset containing 25,000 high-resolution histopathological images across five cancer subtypes, the research explores EfficientNet-B0 and a custom CNN architecture. Images underwent a robust preprocessing pipeline including Contrast Limited Adaptive Histogram Equalization (CLAHE) for local contrast enhancement, pseudo-color mapping to enrich feature representation, normalization for stable convergence, and extensive data augmentation (rotations, shifts, flips, zooms) to improve generalization.

   The research gap arises from the limited focus in prior works on comprehensive preprocessing tailored for medical images; many studies rely solely on raw inputs or simple normalization, often underutilizing texture and color cues crucial for cancer identification. Results show EfficientNet-B0 achieving 99.97% accuracy for lung cancer and 100% for colon cancer, outperforming established pre-trained models like Inception, VGG19, and MobileNet. The custom CNN also achieved near-perfect results (lung: 99.40%, colon: 100%), validating the effectiveness of lightweight architectures when combined with rigorous preprocessing.

   The study's contribution lies in demonstrating that preprocessing enhancements amplify deep learning's discriminative power, narrowing the gap between research-grade and deployable clinical systems. Furthermore, the evaluation incorporated fine-tuned hyperparameters (learning rate scheduling, dropout, and batch normalization) that stabilized training and reduced overfitting. Future directions include validating on whole-slide images, ensuring model robustness against cross-center variability, and exploring multimodal integration with genomic or radiological data for holistic cancer diagnostics.

2. **Exploring Sleep Disorders: A Comparative Analysis of Machine Learning Algorithms on Sleep Health and Lifestyle Data** [2]

   This research tackles the critical challenge of accurately classifying sleep disorders, conditions such as insomnia, apnea, and circadian rhythm disturbances that significantly affect human health. Traditional polysomnography-based diagnosis is time-intensive and error-prone, creating a demand for automated solutions. Using the publicly available Sleep Health and Lifestyle Dataset comprising features such as BMI, blood pressure, occupation, stress levels, and physical activity, the study evaluates machine learning algorithms (Random Forest, AdaBoost, Logistic Regression, and Gradient Boosting) to improve classification accuracy. Preprocessing steps included label encoding of categorical variables, MinMax scaling for normalization, and k-fold cross-validation with hyperparameter tuning to mitigate overfitting.

   The research gap lies in the under-explored application of ensemble methods with robust tuning on lifestyle-driven health data, as most prior works focus narrowly on

EEG/ECG signals or single-institution datasets. Results showed Gradient Boosting as superior, achieving 93.8% accuracy, attributed to its ability to build sequential weak learners that capture complex nonlinear patterns. Random Forest and AdaBoost achieved 90–91%, while Logistic Regression provided competitive but less robust results.

The study's contribution is a validated framework demonstrating that well-tuned gradient boosting can outperform both traditional linear models and other ensembles on tabular biomedical-lifestyle data. Implications include the potential deployment of lightweight, scalable ML tools for preliminary sleep disorder screening outside hospital settings, reducing reliance on costly clinical infrastructure. Moreover, the study highlights correlations such as the link between occupation and sleep quality, opening avenues for personalized lifestyle interventions. Future work can extend this by integrating multimodal bio-signals, addressing dataset bias by expanding beyond a single clinic, and exploring explainable AI to make predictions interpretable for medical-professionals.

3. **Multiclass Brain Tumor Classification and Segmentation from 2D MR Images: A Deep Learning Approach Using Custom CNN and Residual Attention U-Net** [3]

   This work focuses on the dual tasks of brain tumor classification and segmentation from T1-weighted MRI scans. The study introduces a custom CNN for multiclass classification (gliomas, meningiomas, and pituitary adenomas plus a "no tumor" class) and a Residual Attention U-Net for segmentation. The CNN employs multiple convolutional-batch normalization-pooling blocks, separable convolutions to reduce parameters, dropout for regularization, and real-time augmentation (rotations, flips, shifts) to enhance robustness. Compared against pre-trained models (VGG16, ResNet50, EfficientNet-B1, and Xception), the custom CNN achieved a classification accuracy of 99.46%, outperforming transfer learning approaches, particularly with limited training samples.

   For segmentation, the proposed Residual Attention U-Net extends the traditional U-Net by embedding residual blocks and attention gates. These mechanisms emphasize tumor regions while suppressing irrelevant background, mitigating vanishing gradients, and capturing fine-grained spatial details. The model surpassed baseline U-Net and Residual U-Net architectures, especially in handling small tumors.

   The research gap addressed here is twofold: prior studies often treat classification and segmentation separately, and few explore attention-augmented residual mechanisms in U-Net for brain MRIs. The contribution is a unified pipeline achieving state-of-the-art performance in both tasks, while demonstrating efficiency and generalization on publicly available datasets. The framework can be expanded to multimodal MRI inputs (FLAIR, T2), 3D volumetric data, or integrated into federated learning settings to leverage multi-institutional datasets while preserving privacy.

# References

[1] A. Taher, W. I. Z. Ayon, and M. S. Hossain, "Histopathological Image-Based Classification of Lung and Colon Cancer Using Deep Learning Architectures with

Preprocessing Enhancements," in Proceedings of the 27th International Conference on Computer and Information Technology (ICCIT), 2024. DOI: 10.1109/ICCIT64611.2024.11022478.

[2] A. Taher and W. I. Z. Ayon, "Exploring Sleep Disorders: A Comparative Analysis of Machine Learning Algorithms on Sleep Health and Lifestyle Data," 2024 IEEE International Conference on Power, Electrical, Electronics, and Industrial Applications (PEEIACON-24), 2024. DOI: 10.1109/PEEIACON63629.2024.10800593.

[3] A. Taher and S. Anan, "Multiclass Brain Tumor Classification and Segmentation from 2D MR Images: A Deep Learning Approach Using Custom CNN and Residual Attention U-Net," 26th International Conference on Computer and Information Technology (ICCIT), pp. 1-6, 2023. DOI: 10.1109/ICCIT60459.2023.10441606.