Research Publications

1. **Early Detection of Diabetic Retinopathy using Novel Pre-Processing of Retinal Fundus Images** [1]

   This paper presents an automated deep learning framework for binary classification of Diabetic Retinopathy (DR) from retinal fundus images, with its core novelty lying in a carefully designed eleven-step preprocessing pipeline that transforms raw fundus photographs into structurally enriched three-channel composite images. Instead of using conventional RGB input, the pipeline extracts three physiologically meaningful layers — thick retinal vessels through Gaussian low-pass subtraction, fine vessels through Frangi filtering using the Hessian matrix, and retinal lesions through morphological Top-Hat and Black-Hat transformations that separately capture bright exudates and dark hemorrhages — and merges them into a single composite input. The preprocessing further incorporates bilateral filtering for edge-preserving noise reduction, CLAHE for local contrast enhancement, auto-cropping, image dehazing, green channel extraction, and a final circular crop with Lanczos4 resizing to 512×512 pixels.

   On the model side, a fine-tuned InceptionV3 backbone is augmented with a custom 1×1 spatial attention layer placed immediately after the feature extractor, which generates attention weights through a sigmoid activation and modulates feature maps element-wise, guiding the network to focus on clinically relevant retinal regions. Training is conducted in two phases — an initial feature extraction phase with all InceptionV3 layers frozen, followed by a fine-tuning phase where layers beyond layer 249 are unfrozen — using the Adam optimizer with Binary Cross-Entropy loss, early stopping, and model checkpointing.

   The combined APTOS-2019 and Messidor-2 dataset was relabeled into DR and Non-DR classes with an 80:20 patient-level split, and data augmentation including rotation, flipping, zoom, and shift was applied during training. The proposed framework achieved an accuracy of 99.54%, precision of 99.49%, recall of 99.56%, F1-score of 99.52%, and an AUC of 99.91%, demonstrating that integrating domain-informed handcrafted preprocessing with attention-guided deep learning produces a highly accurate and generalizable system well-suited for clinical DR screening.

2. **An Explainable Ensemble Framework for Multi-Level Diabetic Retinopathy Classification** [2]

   This paper presents a comprehensive deep learning framework that addresses Diabetic Retinopathy classification at three levels of granularity simultaneously — binary (DR vs. Non-DR), ternary (Non-DR, Non-Proliferative DR, and Proliferative DR), and five-class severity grading — using the APTOS-2019 dataset. The preprocessing pipeline performs circular region-of-interest cropping, green channel extraction, CLAHE contrast enhancement with gamma correction, median blur smoothing, and pixel normalization, producing standardized 224×224 inputs for all tasks.

   The architectural novelty lies in a lightweight Spatial Attention Module (SAM) integrated after the final convolutional block of five ImageNet-pretrained CNN backbones — AlexNet, ResNet-50, DenseNet-121, GoogLeNet, and EfficientNet-B5 —

where the SAM aggregates channel-wise average and max-pooled features, concatenates them, and passes them through a 7×7 convolution with sigmoid activation to generate a 2D attention map that recovers fine-grained lesion details often suppressed by standard global pooling.

To further improve robustness, a Soft Voting Ensemble strategy is employed for each classification task by selecting the two best-performing backbone models based on validation accuracy and averaging their posterior probability vectors, allowing confident model predictions to compensate for uncertain ones. Class imbalance in the APTOS-2019 dataset is handled through a weighted cross-entropy loss inversely proportional to class frequency, and training uses Adam optimization with early stopping.

Explainability is incorporated through Grad-CAM and Grad-CAM++ visualizations, which confirm that the model correctly localizes pathologically significant regions such as microaneurysms and hemorrhages, bridging the gap between black-box predictions and clinical trust. The ensemble framework achieved accuracies of 99.46% for binary classification, 91.55% for ternary classification, and 83.65% for five-class grading, with Quadratic Weighted Kappa scores of 0.9892, 0.8933, and 0.8749 respectively, consistently outperforming all individual backbone models across every task.

3. **Gamma-CLAHE Enhanced InceptionV3 for Alzheimer's and Parkinson's Disease Detection with Explainable MRI Insights** [3]

This paper proposes a multi-class classification framework for simultaneously distinguishing Alzheimer's Disease (AD), Parkinson's Disease (PD), and healthy control subjects from brain MRI scans, addressing the challenge that both neurodegenerative conditions share subtle and overlapping structural features that make automated differentiation particularly difficult. The central preprocessing contribution is a novel Gamma-CLAHE hybrid technique applied in the LAB color space — CLAHE is first applied to the luminance channel for localized contrast enhancement, followed by gamma correction with an optimal value of $\gamma = 1.3$ to non-linearly adjust image brightness and recover structural details, after which the enhanced channel is merged back with the color channels.

This combination was systematically evaluated against three alternative hybrid methods — Weighted-CLAHE, CLAHE with bilateral filter, and CLAHE with median filter — and consistently outperformed all of them, establishing Gamma-CLAHE as the most effective preprocessing strategy for this task. An important empirical finding of the paper is that resizing MRI images to 150×150 pixels outperforms the commonly used 224×224 resolution, because MRI scans contain homogeneous grayscale regions with fine intensity gradients that get diluted and noised at larger resolutions, causing an accuracy drop.

The model architecture builds on InceptionV3 pretrained on ImageNet, with its classification head replaced by a Global Average Pooling layer, a Dropout layer with rate 0.5, and a three-neuron Softmax output layer for multi-class prediction. The model is trained using the Adam optimizer with categorical cross-entropy loss, early stopping, and a ReduceLROnPlateau scheduler, on a Kaggle dataset of 7,839

MRI images split 80:10:10 across training, validation, and test sets with mild augmentation (±5° rotation, ±5% shift, ±5% zoom) to preserve anatomical integrity.

Explainability is provided through Grad-CAM visualizations that highlight class-specific brain regions driving each prediction, making the model's decisions transparent and interpretable for clinicians. The proposed framework achieved a test accuracy of 98.85% with precision, recall, and F1-scores consistently at 0.98–0.99 across all three classes, correctly classifying 364 of 367 control subjects, 315 of 320 AD patients, and 96 of 97 PD patients.

4. **Histopathological Image-Based Classification of Lung and Colon Cancer Using Deep Learning Architectures with Preprocessing Enhancements** [4]

   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.

5. **Exploring Sleep Disorders: A Comparative Analysis of Machine Learning Algorithms on Sleep Health and Lifestyle Data** [5]

   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.

6. **Multiclass Brain Tumor Classification and Segmentation from 2D MR Images: A Deep Learning Approach Using Custom CNN and Residual Attention U-Net** [6]

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

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