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Name of Candidate: *Anupam Kumar*
Name of Supervisor: *Dr. Faiyaz Ahmad*
Co-Supervisor (if applicable): *Prof. (Dr.) Bashir Alam*
Name of the Department: Computer Engineering
Faculty: Faculty of Engineering and Technology

Research Topic: Hybrid Bio-Inspired Computing in Medical Image Data Analysis

Findings

Early and accurate diagnosis of life-threatening diseases such as Alzheimer's disease, lung disorders, and breast cancer remains a major challenge in modern healthcare due to limited expert availability, high inter-observer variability, and the growing volume of medical imaging data. Deep learning models have demonstrated strong feature learning capability; however, their performance is often constrained by redundant features, high computational complexity, limited generalizability, and suboptimal decision boundaries when applied directly to clinical imaging data. Addressing these challenges is essential for developing reliable, scalable, and clinically deployable diagnostic systems, particularly in telemedicine and resource-constrained settings.

To overcome these limitations, this research proposes a series of hybrid frameworks that integrate deep convolutional neural networks (CNNs) with bio-inspired and quantum-inspired optimization algorithms for feature selection, parameter optimization, and robust classification. The proposed methodologies are systematically designed to enhance classification accuracy, reduce feature dimensionality, improve convergence behavior, and ensure computational efficiency across multiple medical imaging modalities.

In the first phase, deep CNN architectures such as DenseNet, MobileNet, VGG, ResNet, and Inception are employed for automated feature extraction from medical images, including MRI, chest X-ray, CT, and histopathological images. Extensive benchmarking reveals that while CNNs achieve high representational capability, direct end-to-end classification often leads to redundant feature utilization and unstable decision boundaries, motivating the integration of optimization-driven feature refinement mechanisms.

In the second phase, hybrid bio-inspired optimization algorithms—such as Particle Swarm Optimization (PSO), Genetic Algorithm (GA), and Neural Stem Cell Optimization (NSCO)—are integrated with deep features to perform optimal feature selection. These algorithms effectively eliminate irrelevant and correlated features while preserving diagnostically significant patterns. The optimized feature subsets significantly reduce computational overhead and enhance classification robustness. Comparative evaluations against standalone CNN models and conventional hybrid approaches demonstrate consistent improvements in accuracy, precision, recall, and F1-score across binary and multi-class classification tasks.

In the third phase, an advanced quantum-inspired optimization framework is introduced to further enhance exploration–exploitation balance during feature selection. The proposed Quantum-Inspired NSCO (QNSCO) mechanism improves convergence speed and avoids premature stagnation, leading to superior performance on challenging and imbalanced datasets such as BreaKHis and Alzheimer's MRI repositories. A Support Vector Machine (SVM) classifier is employed in the final stage to establish non-linear decision boundaries, ensuring stable and interpretable classification outcomes.

The proposed frameworks are rigorously evaluated using comprehensive performance metrics, including accuracy, sensitivity, specificity, precision, recall, F1-score, ROC-AUC, and computational efficiency. Experimental results consistently demonstrate that the hybrid deep learning–optimization models outperform existing state-of-the-art methods in terms of diagnostic accuracy, generalization capability, and robustness. Reported classification accuracies exceed 98% for binary tasks and show substantial gains for multi-class disease classification scenarios.

Collectively, the research presents a unified and adaptive diagnostic framework that addresses critical challenges in medical image analysis—namely high-dimensional feature spaces, limited labeled data, and deployment constraints in telehealth environments. By combining deep representation learning with intelligent bio-inspired optimization, the proposed models ensure reliable, scalable, and clinically meaningful decision support.

The effectiveness of the proposed approaches is validated through extensive simulations and experimental studies, confirming their suitability for real-time telemedicine applications, where early diagnosis, reduced computational cost, and high diagnostic confidence are paramount. The outcomes of this research contribute significantly to the advancement of

intelligent healthcare systems and provide a strong foundation for future research in AI-driven medical diagnostics.

Keywords:
Deep Learning, Bio-Inspired Optimization, Medical Image Analysis, Feature Selection, Telemedicine, Disease Classification