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Multi-Disease Neurodiagnostic Assistant Using Deep Learning

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Abstract: The increasing prevalence of neurological disorders such as brain tumors, Alzheimer's disease, and Parkinson's disease requires the development of automated diagnostic systems. Traditional methods rely heavily on the expert interpretation of MRI scans, which can be time-consuming and prone to human error.
This paper presents a deep learning-based framework for multi-disease brain diagnosis using transfer learning with ResNet50 and a hybrid optimization technique combining Par- ticle Swarm Optimization (PSO) and Genetic Algorithm (GA). The proposed model automatically tunes hyperparameters such as the learning rate, the dropout rate, and the dense layer size using the validation accuracy as the fitness function.
Experimental results demonstrate that the hybrid PSO-GA approach improves model performance and generalization compared to manually tuned systems. The framework provides a scalable and efficient solution for medical image classification.
Index Terms: Deep Learning, ResNet50, PSO, Genetic Algo- rithm, Brain Tumor, Medical Imaging, Optimization.

I. INTRODUCTION

Neurological disorders such as brain tumors, Alzheimer's disease, and Parkinson's disease have emerged as major global health challenges, significantly impacting mortality rates and quality of life. Early and accurate diagnosis plays a crucial role in improving treatment outcomes and patient survival rates. Magnetic Resonance Imaging (MRI) is widely used as a non- invasive imaging technique for detecting abnormalities in brain structures. However, manual interpretation of MRI scans is time-consuming, requires expert knowledge, and is prone to human error. With the rapid advancement of Artificial Intelligence (AI), deep learning techniques have revolutionized medical image analysis. Convolutional Neural Networks (CNNs) are capable of automatically extracting complex features from images and performing classification tasks with high accuracy. Among these, transfer learning approaches using pre-trained models such as ResNet50 have shown significant improvements in performance while reducing training time. Despite these advancements, selecting optimal hyperparameters such as learning rate, dropout rate, and network architecture remains a challenging task. Improper tuning can lead to overfitting or underfitting, thereby affecting model generalization. To address this issue, this paper proposes a hybrid optimization approach that combines Particle Swarm Optimization (PSO) and Genetic Algorithm (GA) for auto- mated hyperparameter tuning. The proposed NeuroDiag system integrates deep learning with hybrid optimization to provide an efficient, scalable, and accurate solution for multi-disease brain diagnosis.

II. LITERATURE SURVEY

Recent advancements in deep learning have significantly improved the performance of medical image classification systems. Pre-trained convolutional neural networks such as VGGNet, Inception, and ResNet have been widely used for feature extraction due to their ability to capture complex spatial patterns in medical images.

ResNet50, in particular, has gained popularity due to its residual learning framework, which helps overcome the van- ishing gradient problem in deep networks. Studies have shown that transfer learning using ResNet architectures achieves higher accuracy compared to traditional CNN models. In addition to model selection, hyperparameter optimization plays a crucial role in improving performance. Genetic Algo- rithms (GA) have been widely used for global optimization due to their ability to explore large search spaces. Similarly, Particle Swarm Optimization (PSO) has been applied for fast convergence and efficient parameter tuning.

However, most existing approaches utilize either GA or PSO independently. The combination of both techniques in a hybrid PSO-GA framework provides a balance between exploration and exploitation, leading to improved optimization performance. This paper builds upon these concepts by integrating deep learning with hybrid optimization for multi-disease brain classification.

III. DATASET DESCRIPTION

The proposed NeuroDiag system utilizes multiple publicly available MRI image datasets collected from open medical repositories. The datasets are organized to support classifi- cation of three major neurological disorders: brain tumor, Alzheimer's disease, and Parkinson's disease.

A. Brain Tumor Dataset

The brain tumor dataset consists of MRI images catego- rized into four classes: glioma, meningioma, pituitary tumor, and normal brain. These images are obtained from publicly available medical imaging repositories and are widely used for research purposes.

The dataset contains high-resolution MRI scans collected under varying imaging conditions, providing diversity in terms of contrast, orientation, and noise. This variability helps im- prove the generalization capability of the deep learning model.

B. Alzheimer's Disease Dataset

The Alzheimer's dataset contains MRI images representing different stages of cognitive impairment. The dataset is cate- gorized into four classes:

- Non-Demented
- Very Mild Demented
- Mild Demented
- Moderate Demented

These images are obtained from open-access medical datasets and are commonly used for studying the progression of Alzheimer's disease. The dataset provides structural brain changes associated with memory loss and cognitive decline.

C. Parkinson's Disease Dataset

The Parkinson's dataset includes MRI images used to distinguish between healthy individuals and patients affected by Parkinson's disease. The dataset is categorized into two classes:

- Parkinson's Disease
- Healthy Control

The dataset captures structural variations in brain regions associated with motor control. It is sourced from publicly available repositories and is suitable for binary classification tasks.

D. Dataset Summary

TABLE I DATASET SUMMARY

Disease	Data Type	Classes
Brain Tumor	MRI Images	4 Classes
Alzheimer's	MRI Images	4 Classes
Parkinson's	MRI Images	2 Classes

IV. PROBLEM STATEMENT

The primary objective of this work is to develop an au- tomated system capable of accurately classifying multiple neurological disorders using MRI images. The system aims to address several key challenges in medical image analysis.

First, manual diagnosis is time-consuming and requires expert knowledge, making it difficult to scale in real-world scenarios. Second, deep learning models require careful hyper- parameter tuning, which is often performed manually and may not yield optimal results. Third, ensuring model generalization across different datasets remains a significant challenge.

To overcome these limitations, the proposed system focuses on the following objectives:

- Develop a deep learning-based model for multi-disease classification
- Automate hyperparameter tuning using hybrid PSO-GA optimization
- Improve model accuracy and generalization
- Reduce dependency on manual intervention

V. PROPOSED METHODOLOGY

A. *System Architecture*

The proposed NeuroDiag system follows a structured pipeline consisting of multiple stages, including data prepro- cessing, feature extraction, optimization, training, and evalua- tion.

Initially, MRI images are collected and preprocessed to ensure uniformity in size and quality. The processed images are then passed through a pre-trained ResNet50 model, which extracts high-level features. These features are further pro- cessed using fully connected layers for classification.

To enhance model performance, a hybrid PSO-GA opti- mization algorithm is employed to automatically tune critical hyperparameters such as learning rate, dropout rate, and dense layer size. The optimized model is then trained and evaluated using validation accuracy as the performance metric.

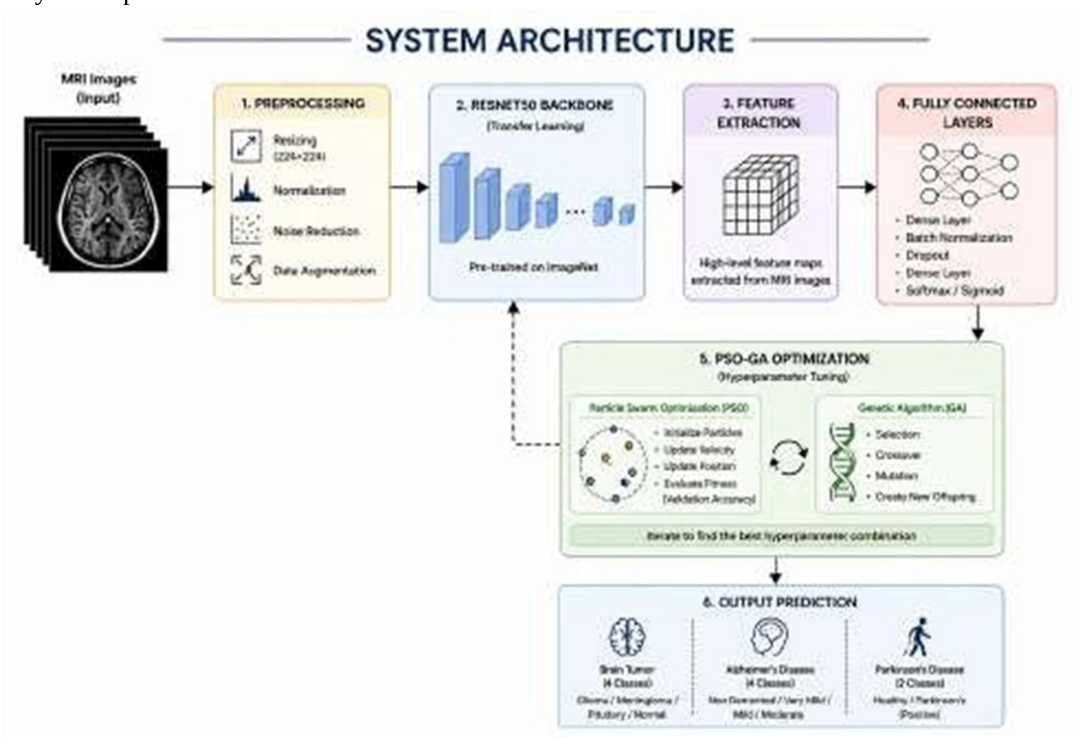

Fig. 1. Overall architecture of the proposed NeuroDiag system.

B. *Data Preprocessing*

Data preprocessing plays a crucial role in improving model performance and generalization. All MRI images are resized to a standard dimension of 224 × 224 pixels to match the input requirements of the ResNet50 model.

Pixel values are normalized to ensure faster convergence during training. Data augmentation techniques such as rota- tion, zooming, and horizontal flipping are applied to increase dataset diversity and reduce overfitting.

The dataset is divided into training, validation, and test sets to ensure proper evaluation of the model.

C. *Model Architecture*

The proposed model utilizes ResNet50 as the base archi- tecture with pre-trained ImageNet weights. Transfer learning allows the model to leverage previously learned features, reducing training time and improving performance.

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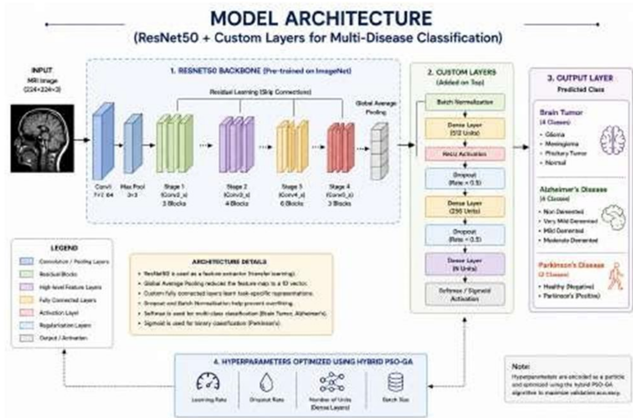

Fig. 2. Modified ResNet50 architecture with additional layers for classifica- tion.

The final layers of the network are modified to suit the classification task. A Global Average Pooling layer is used to reduce spatial dimensions, followed by Batch Normalization to stabilize training.

Fully connected dense layers are added to learn complex patterns, along with Dropout layers to prevent overfitting. The final output layer uses a softmax activation function to classify the input into multiple disease categories.

VI. HYBRID PSO-GA OPTIMIZATION

Hyperparameter optimization plays a crucial role in improv- ing the performance of deep learning models. Selecting ap- propriate values for parameters such as learning rate, dropout rate, and dense layer size significantly affects model accuracy and generalization. Manual tuning of these parameters is time- consuming and often leads to suboptimal results. To address this issue, a hybrid optimization approach combining Particle Swarm Optimization (PSO) and Genetic Algorithm (GA) is proposed.

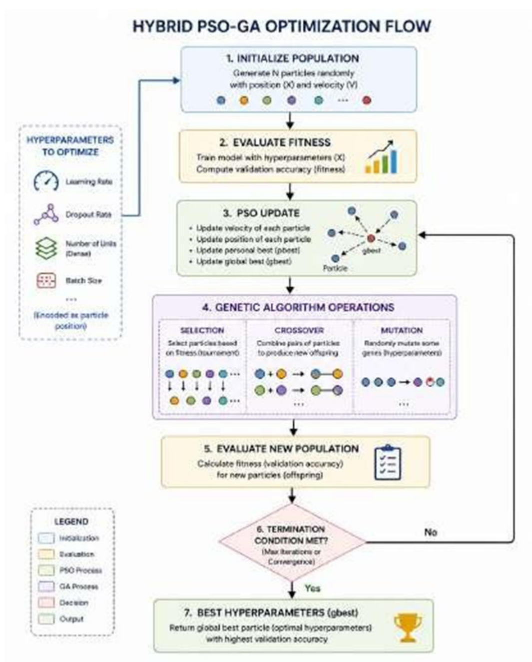

Fig. 3. Hybrid PSO-GA optimization workflow for hyperparameter tuning.

A. *Particle Swarm Optimization*

Particle Swarm Optimization is a population-based opti- mization technique inspired by the social behavior of birds flocking or fish schooling. In PSO, each particle represents a candidate solution in the search space. Each particle updates its position based on its own experience (personal best) and the experience of neighboring particles (global best).

Each particle is defined as:

$$X = (lr, dropout, units) \quad (1)$$

where *lr* represents the learning rate, *dropout* represents the dropout rate, and *units* represents the number of neurons in the dense layer.

The velocity update equation is given by:

$$v_i = wv_i + c_1 r_1 (pbest_i - x_i) + c_2 r_2 (gbest - x_i) \quad (2)$$

The position update is defined as:

$$x_i = x_i + v_i \quad (3)$$

Here, w is the inertia weight, c_1 and c_2 are acceleration coefficients, and r_1, r_2 are random values.

B. Genetic Algorithm

Genetic Algorithm is an evolutionary optimization tech- nique based on the principles of natural selection. It operates on a population of candidate solutions and evolves them over generations using genetic operators.

The main operations in GA include:

- Selection: Choosing the best-performing individuals based on fitness
- Crossover: Combining two parent solutions to create offspring
- Mutation: Introducing random changes to maintain di- versity

These operations help in exploring the search space and avoiding local minima.

C. Hybrid PSO-GA Approach

The hybrid PSO-GA approach combines the strengths of both optimization techniques to achieve better performance. PSO provides fast convergence by guiding particles towards promising regions of the search space, while GA enhances exploration through crossover and mutation.

The optimization process begins with initializing a popula- tion of particles. Each particle is evaluated using a fitness func- tion based on validation accuracy. PSO is applied to update particle velocities and positions, followed by GA operations to introduce diversity in the population.

This hybrid approach ensures a balance between exploration and exploitation, leading to improved optimization perfor- mance and better convergence.

D. Fitness Function

The fitness of each particle is evaluated using validation accuracy obtained from the deep learning model:

$$Fitness = \max(Validation\ Accuracy) \quad (4)$$

Higher fitness values indicate better-performing hyperpa- rameter configurations.

E. Optimization Workflow

The overall optimization process can be summarized as follows:

1) Initialize particles randomly within the search space
2) Decode particle positions into hyperparameters
3) Train the model and evaluate validation accuracy
4) Update personal best and global best
5) Apply PSO updates to velocity and position
6) Perform GA crossover and mutation
7) Repeat for multiple generations

The best-performing hyperparameters are selected and used to train the final model.

VII. PROPOSED ALGORITHM

The hybrid PSO-GA optimization process used in the pro- posed system is summarized in Algorithm 1.

1) Initialize a population of particles with random positions and velocities
2) Decode each particle into hyperparameters (learning rate, dropout, dense units)
3) Train the deep learning model using the given parame- ters

4) Evaluate fitness using validation accuracy
5) Update personal best (pbest) and global best (gbest)
6) Update particle velocity and position using PSO equa- tions
7) Select top-performing particles
8) Apply Genetic Algorithm operations:
    - Perform crossover between selected particles
    - Apply mutation to introduce randomness
9) Replace old population with new offspring
10) Repeat steps 2–9 for multiple generations
11) Return best hyperparameters (gbest)

VIII. IMPLEMENTATION

The proposed NeuroDiag system is implemented using Python and deep learning frameworks such as TensorFlow and Keras. The development and experimentation are carried out in the Google Colab environment, which provides GPU support for accelerating the training process.

The dataset is organized into structured directories con- sisting of training, validation, and testing sets. Image pre- processing techniques such as resizing, normalization, and augmentation are applied to improve model generalization and reduce overfitting. Data augmentation includes operations such as rotation, flipping, zooming, and shifting.

The ResNet50 model is used as the base architecture with pre-trained ImageNet weights. The final layers are modified to suit the multi-class classification problem. Additional layers such as Global Average Pooling, Batch Normalization, Dense layers, and Dropout are incorporated to enhance performance. The hybrid PSO-GA optimization algorithm is integrated into the training pipeline, where multiple hyperparameter com- binations are evaluated dynamically. The best configuration obtained from optimization is used to train the final model.

IX. RESULTS AND ANALYSIS

The performance of the proposed model is evaluated using validation accuracy as the primary metric. The hybrid PSO-GA optimization algorithm successfully identifies optimal hyper- parameters that significantly improve model performance.

The optimized model achieved a validation accuracy of approximately 80%, demonstrating a notable improvement compared to manually tuned models. The optimization process effectively balances exploration and exploitation, leading to better convergence.

Training and validation curves indicate stable learning be- havior with reduced overfitting. The model shows consistent improvement across epochs, confirming the effectiveness of the proposed approach.

The results validate that combining transfer learning with hybrid optimization techniques leads to improved classification accuracy and better generalization across multiple datasets.

A. Alzheimer's Disease Classification

The Alzheimer's disease classification model was evalu- ated using multi-class MRI datasets. The model successfully distinguishes between different stages of dementia with high confidence.

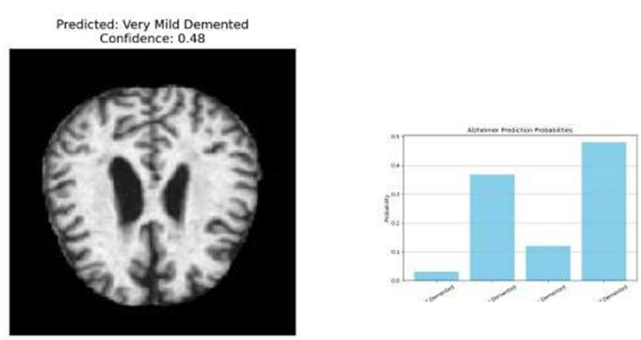

Fig. 4. Alzheimer disease prediction output and probability distribution.

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The results demonstrate that the model effectively captures structural brain variations associated with different stages of Alzheimer's disease. The probability distribution further confirms the confidence of the model in its predictions.

B. Brain Tumor Classification

The brain tumor classification model was trained to classify MRI images into multiple tumor categories and normal cases. The use of transfer learning with ResNet50 significantly enhances feature extraction.

C. Parkinson's Disease Classification

The Parkinson's disease model performs binary classifica- tion to distinguish between healthy individuals and affected patients.

The Parkinson's dataset exhibits slight class imbalance, with a higher proportion of positive samples. This may introduce bias in predictions toward the positive class. Despite this lim- itation, the model demonstrates consistent detection capability and supports the effectiveness of the proposed framework.

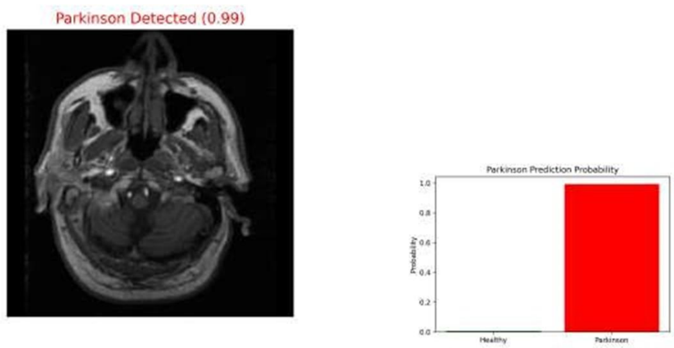

Fig. 6. Parkinson disease prediction output and probability distribution.

The results indicate that the model is capable of identifying patterns associated with Parkinson's disease, although further improvements can be achieved with balanced datasets.

D. Overall Performance

The experimental results confirm that the hybrid PSO- GA optimization approach effectively enhances model perfor- mance by selecting optimal hyperparameters. The combination of transfer learning and evolutionary optimization results in improved accuracy, better generalization, and stable training behavior.

Overall, the proposed NeuroDiag system demonstrates strong potential for automated multi-disease brain diagnosis and provides a scalable solution for medical image classification.

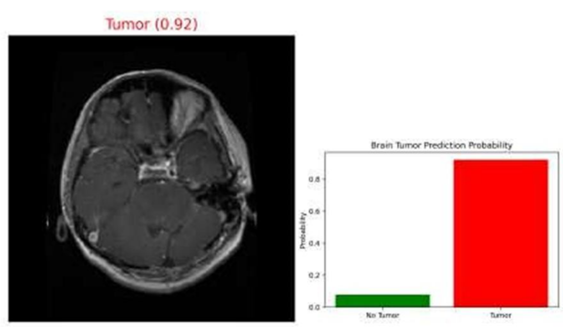

Fig. 5. Brain tumor classification output and probability distribution.

The model successfully identifies tumor types such as glioma, meningioma, and pituitary tumors. The results indicate strong classification capability and improved performance due to optimized hyperparameters.

X. DISCUSSION

The experimental results demonstrate that integrating deep learning with hybrid optimization techniques significantly en- hances model performance. The PSO-GA approach effectively explores the hyperparameter space and identifies optimal con- figurations.

Compared to traditional manual tuning methods, the pro- posed approach provides a systematic and automated solution. The fast convergence property of PSO combined with the exploration capability of GA ensures a balanced optimization process.

However, the optimization process introduces additional computational complexity due to repeated model training. This may increase execution time, especially for large datasets.

Despite these challenges, the improved accuracy and ro- bustness of the model make the proposed system suitable for real-world medical applications.

XI. CHALLENGES AND SOLUTIONS

During the development of the system, several challenges were encountered. One of the major issues was incorrect dataset path configuration, which resulted in empty dataset loading. This was resolved by properly mounting Google Drive and verifying directory paths. Another challenge was the occurrence of out-of-memory errors during training. This issue was addressed by reducing the batch size and optimizing memory usage. Additionally, class mismatch errors were observed when the number of output neurons did not match the dataset classes. This problem was corrected by adjusting the final layer size. These solutions ensured stable execution and improved model performance.

XII. ADVANTAGES

The proposed system offers several advantages over tradi- tional approaches. The use of hybrid PSO-GA optimization eliminates the need for manual hyperparameter tuning, making the system more efficient and automated.

Transfer learning using ResNet50 reduces training time while maintaining high accuracy. The system is scalable and can be extended to include additional diseases and datasets. Furthermore, the integration of optimization techniques im- proves model generalization and robustness.

XIII. LIMITATIONS

Despite its advantages, the proposed system has certain limitations. The hybrid optimization process increases compu- tational cost, requiring GPU resources for efficient execution. The performance of the model is dependent on dataset quality and diversity. Limited or imbalanced datasets may affect accuracy and generalization. Additionally, the system focuses only on image-based data and does not incorporate other clinical information.

XIV. FUTURE WORK

Future work can focus on developing a real-time diagnosis system using web or mobile applications. The integration of multimodal data such as clinical reports and patient history can further enhance performance.

Advanced deep learning models such as EfficientNet and Vision Transformers can be explored to improve accuracy. Explainable AI techniques can also be incorporated to provide transparency and increase trust in the system. The proposed framework can be extended for deployment in healthcare environments to assist medical professionals.

XV. CONCLUSION

This paper presents NeuroDiag, a deep learning-based framework for multi-disease brain diagnosis using hybrid PSO-GA optimization. The proposed system effectively com- bines transfer learning with evolutionary optimization tech- niques to improve classification performance. The results demonstrate that the hybrid approach enhances accuracy and generalization compared to traditional methods. The system provides a scalable and efficient solution for automated medical image classification.

Overall, the proposed framework has strong potential for real-world applications and can contribute to early diagnosis and improved healthcare outcomes.

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