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Evolutionary CNN Channel Selection Using Online Genetic Algorithm: Brain Tumor MRI as a Case Study

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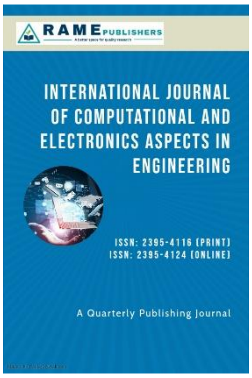

Abstract- Deep convolutional neural networks generate huge of feature channels many of these features have limited discriminative information. Nowadays numerous optimization techniques have been proposed for deep feature selection and most of them are offline operation. This paper presents an online evolutionary method for CNN channel selection based on Hasan's Online Genetic Algorithm (OGA), where the optimization process operates directly on the channel representation extracted from a deep convolutional network. To evaluate the proposed approach, deep feature maps were extracted using a pretrained ResNet50 network and converted into channel descriptors through global average pooling then Hasan's OGA was applied to optimize channel selection, and the resulting channel subset was evaluated using a Support Vector Machine (SVM) classifier. Experimental evaluation on a publicly available four-class brain tumor MRI dataset demonstrated that the proposed evolutionary optimization reduced the original 2048-channel representation to only 954 channels, corresponding to a channel reduction ratio of 53.42%. Despite eliminating more than half of the available channels, the optimized representation achieved a test classification accuracy of 93.19%, with precision 93.82%, recall 93.19%, and F1-score 92.98%. The obtained results showed that proposed algorithm provides an effective and computationally efficient method to select channels in deep CNN, where it reduces channel redundancy by eliminating the useful channel and keeping only the effected ones.

Keywords— Channel Selection, Deep Convolutional Neural Networks, Hasan's Online Genetic Algorithm, Feature Channel Optimization.

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1. Introduction

Deep convolutional neural networks (CNNs) nowadays improve the manipulation of computer vision by enabling automatic extraction of feature representations directly from raw data. Among many architectures of CNN the ResNet50 architecture has become one of the most widely used network because of its residual learning approach, which effectively solve the drawback encountered in very deep neural networks [1]. In present day, pre-trained deep models have demonstrated exceptional capability in producing robust and transferable feature representations suitable for a wide range of classification and recognition tasks [2]–[7]. These pretrained networks enable researchers to exploit rich semantic information while significantly reducing computational cost, training time, and data requirements compared with training deep architectures from scratch.

It is known that CNNs generate hundreds or even thousands of feature channels during the forward propagation process. Each channel captures different visual characteristics; however, not every channel affects the final recognition task. In many practical applications, a considerable proportion of the generated channels exhibit high correlation, redundancy, or limited discriminative value, particularly when pre-trained networks are transferred to application domains that differ from those used during the original training process [8], [9]. Therefore, manipulating all extracted channels may unnecessarily increase computational complexity, memory consumption, and classifier training time while introducing noisy or task-irrelevant information into the learning process.

As deep feature dimensionality continues to grow, the development of efficient optimization techniques capable of identifying informative channel subsets has become an important research direction for improving both computational efficiency and classification performance. The challenge of reducing feature and channel redundancy has therefore attracted increasing attention within the deep learning studies. Instead of redesigning CNN architectures, many recent studies have focused on optimizing the extracted representations by identifying compact subsets of informative descriptors before classification [8]–[13].

Several studies were introduced to reduce memory and processing constraints, Ozdemir et al. [8] enhanced the classification capacity of CNNs by implementing targeted deep feature selection and fusion. Kiraz et al. [9] extracted and reduced the dimensionality of medical image features using combined deep learning architectures and autoencoders. Atteia et al. [10] developed an adaptive dynamic optimization algorithm specifically for feature selection in medical data. Emphasizing computational efficiency, Dar and Ganivada [18] proposed a deep learning framework that combines a pretrained MobileNet feature extractor with a Genetic Algorithm for feature selection and an ensemble classifier for breast ultrasound image classification. Their results demonstrated that evolutionary feature selection can effectively identify informative deep features and improve classification performance.. Hamad et al. [12] optimized pre-trained shallow CNNs for COVID-19 detection. He et al. [27] investigated early channel pruning techniques to accelerate very deep neural networks. Subsequently, Liu et al. [28] proposed MetaPruning to automate channel pruning via meta-learning, and Li et al. [29] developed EagleEye for the rapid evaluation of pruned sub-networks. Humble et al. [30] introduced soft masking techniques for cost-constrained environments, while Li et al. [31] re-evaluated random channel pruning for network compression. Liu et al. [32] presented AdaPruner which is an adaptive channel pruning method utilizing architecture and weight inheritance. Wang et al. [31] improved pruning efficiency using an Improved Grey Wolf Optimizer. Park et al. [34] developed REPrune which is focuses on representative kernel-based reduction, and Chen et al. [32] proposed MLPruner for automatic, mask-learning-based channel removal.

Many researches used the evolutionary algorithm in feature or channel selction, for example, the papers presented by Gochhait [22] and Faizan and Mohammad [23] reviewed the recent integration of metaheuristic algorithms for generalized feature selection. Alsalamah and Ismail [24] presented an algorithm to reduces image dimensions by evolution computation. Zhou et al. [36] developed an evolution multitask approach for convolutional neural architecture search. Genetic Algorithms (GAs) have many advantages in solving the binary optimization problem of feature selection. Dar and Ganivada. [25] proposed an ensemble model based on deep learning and genetic algorithms for medical image classification. Naskar et al. [26] developed an adaptive genetic algorithm dedicated to deep feature selection for lung cancer histopathology.

Although the development in reducing the dimension of feature deep learning several limitations remain. First, most existing methods perform optimization after complete feature extraction or rely on iterative network pruning that requires repeated retraining. Second, channel importance is commonly estimated using deterministic heuristics or layer-wise ranking criteria instead of jointly evaluating channel subsets through global evolutionary search.

In this work an Evolutionary CNN Channel Selection based on Hasan's Online Genetic Algorithm (OGA) [14], [15] proposed. Where, the channel selection formulated as a binary optimization problem operating directly on the channel descriptors extracted from a pretrained ResNet50 network. Continuous online evolution enables efficient exploration of the high-dimensional channel search space without requiring repeated CNN retraining.

The rest of the paper is orginazed as following:- section 2 presented the introduction and some of the related works. Section 3 illustrates the proposed work. Section 4 shows the simulation results. And section 5 conclude the important results.

2. Proposed Methodology

The feature extracted from the pretrained CNN (ResNet50) then the online genetic algorithm performs optimization on its output channel representation. The proposed algorithm consists of four stages, as shown in figure 1. 1- the input images are passed through ResNet50 to get higher-level features in the form of convolutional feature maps. 2- global average pooling is carried out to get a fixed-length feature vector with a single value for every channel in each convolution feature map. 3- use Online Genetic Algorithm (OGA) to optimize the channels among the active feature channels by eliminating the redundant channels and weakly discriminative channels. Finally, 4- the selected features are fed into the SVM to get final classifications.

The optimization engine used in this work is Hasan's Online Genetic Algorithm (OGA) which is developed for online identification and adaptive estimation problems through continuous evolutionary updating with Reserved Elite Population (REP) preservation [14], [15]. In the proposed OGA, each channel is treated as an independent optimization variable whose fitness is evaluated with other channels by wrapper-based evolutionary technique. This approach enables the GA to isolate the nonlinear interactions among channels that are ignored by deterministic ranking or filter-based selection methods.

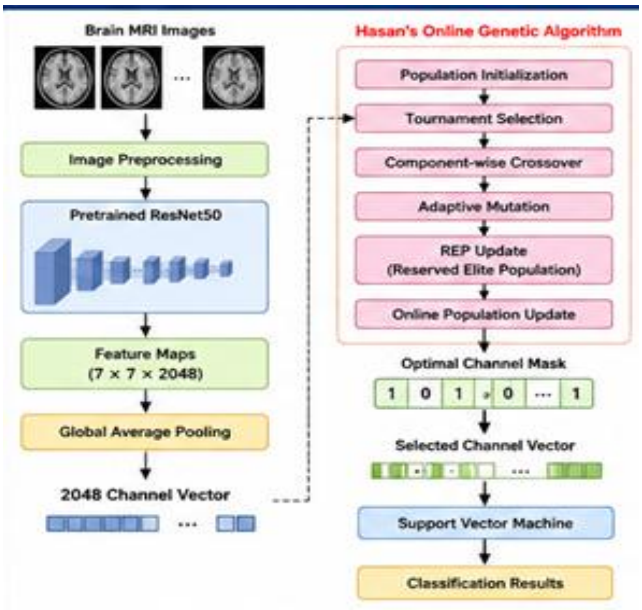

Figure 1. Overall OGA – CNN channel selection algorithm

2.1. Deep CNN Channel Representation

The first stage of the proposed algorithm is extract high-level channel representations using a pretrained convolutional neural network. In this study the network parameters of ResNet50 network remain fixed throughout the optimization process, allowing the evolutionary algorithm to operate exclusively on the extracted channel representations without modifying the pretrained model. As shown in figure 2.

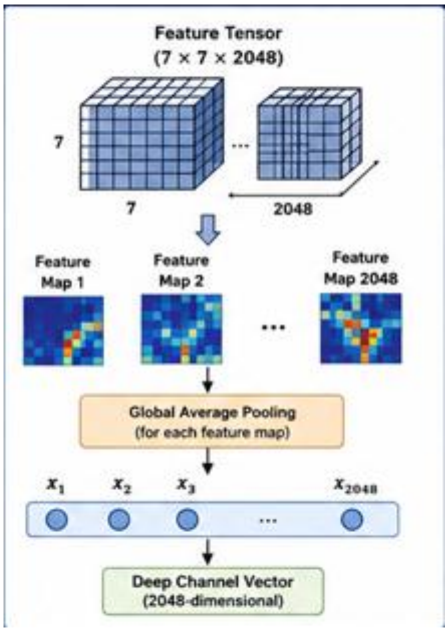

Figure 2. CNN channel representation

Let the input image I be represented as

$$I \in R^{3HW} \tag{1}$$

where **H** and **W** denote the image height and width, respectively.

The pretrained ResNet50 performs a nonlinear mapping from the input image to a high-level feature representation, which can be expressed as

$$F = f(I.\theta) \tag{2}$$

where **f(·)** represents the pretrained ResNet50 network, **θ** denotes the fixed network parameters, and **F** is the output feature tensor generated by the last convolutional block.

For an input image resized to **224 × 224** pixels, the output feature tensor has dimensions

$$F \in R^{7\times7\times2048} \tag{3}$$

indicating that the extracted representation consists of **2048** feature channels, each having a spatial resolution of **7 × 7**.

The complete feature tensor can therefore be written as

$$F = \{F_1.F_2.\dots.F_{2024}\} \tag{4}$$

where $\mathbf{F_i}$ denotes the feature map corresponding to the *i*-th convolutional channel.

To transform each feature map into a compact numerical descriptor, Global Average Pooling (GAP) is applied independently to every channel. The descriptor of the *i*-th channel is calculated as

$$x_i = \frac{1}{HW}\sum\sum F_i(u.v) \tag{5}$$

where the summation is performed over all spatial locations of the feature map. Since the last convolutional layer of ResNet50 produces feature maps of size **7 × 7**, the averaging operation is performed over 49 activation values for each channel.

the final deep channel representation generates by applying Global Average Pooling to all feature channels:

$$x = [x_1.x_2.\dots.x_{2024}] \tag{6}$$

which will be the search space explored by the proposed optimization algorithm.

2.2. Hasan's Online Genetic Algorithm for CNN Channel Selection

The proposed work is based on Hasan's Online Genetic Algorithm (OGA), originally developed for online identification and adaptive estimation problems [14], [15]. Unlike conventional genetic algorithms OGA used an online evolutionary strategy in which candidate solutions are continuously evaluated, updated, and incorporated into the search process. This mechanism enables the algorithm to maintain a dynamic search behavior while keeping the best candidate solutions throughout the optimization process.

In the proposed framework, OGA is reformulated for binary CNN channel selection without modifying its original optimization philosophy. Each chromosome represents a binary channel-selection mask and the evolutionary search aims to identify the subset of channels that maximizes the classification performance while minimizing channel redundancy.

2.2.1 Population Initialization

The optimization begins by generating an initial population consisting of **P** chromosomes,

$$P = \{C_1.C_2.\dots.C_p\} \tag{7}$$

where each chromosome C is generated randomly according to a binary probability distribution. Every chromosome represents one candidate subset of CNN channels.

A candidate solution (chromosome) is represented as

$$C = [c_1.c_2.\dots.c_{2048}] \tag{8}$$

where each gene $\mathbf{c_i}$ is defined as

$$c_i = \begin{cases} 1.\, if\ the\ i-th\ channel\ is\ selected \\ 0.\, otherwise \end{cases} \tag{9}$$

Thus, the chromosome length is equal to the number of channels generated by the pretrained ResNet50 model. Each chromosome therefore represents one possible channel subset that will be evaluated during the evolutionary optimization process, as shown in figure 3.

2.2.2 Reserved Elite Population (REP)

One of the distinguishing characteristics of Hasan's Online Genetic Algorithm is the Reserved Elite Population (REP). Instead of preserving only the best chromosome of the current generation, REP maintains a separate repository containing the highest-quality solutions discovered during the entire optimization process.

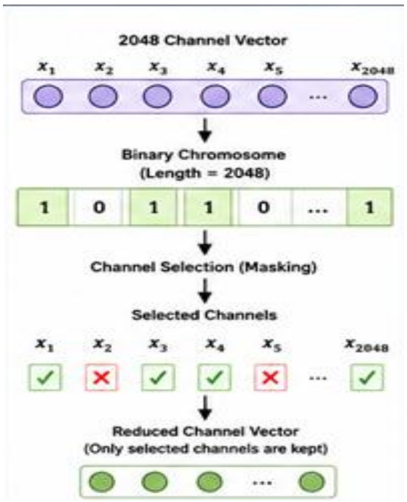

Fig. 3: Binary chromosome representation (Channel selection mask)

The Reserved Elite Population is represented as

$$REP = \{E_1. E_2. \dots . E_r\} \qquad (10)$$

where **r** denotes the REP capacity.

Whenever a newly evaluated chromosome achieves a fitness value greater than the weakest member of the elite repository, the repository is updated by replacing the inferior solution with the newly discovered chromosome. Consequently, REP continuously preserves the globally best candidate solutions while maintaining diversity among elite individuals. Unlike conventional elitism, which is restricted to generation boundaries, the REP mechanism performs continuous online updating throughout the optimization process, thereby reducing the probability of losing highly informative channel subsets.

2.2.3 Evolutionary Cycle

The complete optimization cycle consists of as shown in figure 4.

1. Population evaluation.
2. REP updating.
3. Tournament selection.
4. Component-wise crossover.
5. Adaptive mutation.
6. Fitness evaluation.
7. Online population updating.

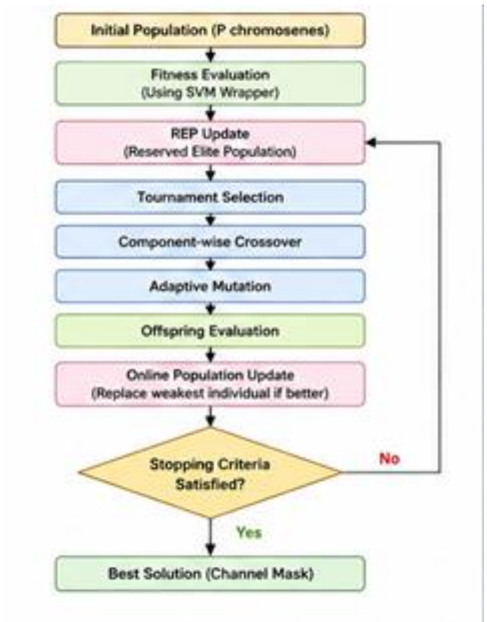

Figure 4. Hasan's Online Genetic Algorithm Flowchart

The complete optimization process of the proposed Evolutionary CNN Channel Selection Framework is summarized in fig 1. The procedure combines deep feature extraction with Hasan's Online Genetic Algorithm to identify an informative subset of CNN channels while preserving high classification performance.

Initially, deep channel representations are extracted from all training images using the pretrained ResNet50 network. Global Average Pooling is subsequently applied to transform the feature maps into a fixed-length channel descriptor consisting of 2048 channels. These descriptors constitute the search space explored by Hasan's Online Genetic Algorithm.

The optimization begins by generating an initial population of binary chromosomes, where each chromosome represents a candidate channel-selection mask. Every chromosome is evaluated using the wrapper-based fitness function, where the objective of the optimization process is to maximize the discriminative capability of the selected channel subset while simultaneously reducing channel redundancy. Accordingly, the optimization problem is formulated as

$$maxFitness(C) \tag{11}$$

subject to

$$1 \leq N_s \leq 2048 \tag{12}$$

where , $\mathbf{N_s}$ denotes the total number of active channels. The number of selected channels contained in a chromosome is calculated as

$$N_s = \sum c_i \tag{13}$$

ensuring that at least one informative channel is preserved while allowing the optimization algorithm to determine the most appropriate subset size automatically.

$$Fitness = \alpha \times Accuracy + (1 - \alpha) \times Reduction \tag{14}$$

where, $\alpha = 0.9$ constant; $Accuracy$ = validation accuracy of the SVM classifier; and $Reduction$ = proportion of removed CNN channels.

$$Reduction = 1 - \frac{N_S}{N} \tag{15}$$

where $N = 2048$.

The resulting fitness values are then used to initialize the Reserved Elite Population (REP), which continuously stores the best solutions discovered during the optimization process.

During each optimization cycle, parent chromosomes are selected using tournament selection. New offspring are generated through component-wise crossover and adaptive binary mutation. After evaluation, the offspring is immediately compared with the weakest individual in the current population. If its fitness is superior, it replaces the weakest chromosome. Simultaneously, the Reserved Elite Population is updated whenever a newly generated chromosome outperforms the weakest elite solution.

Every newly discovered high-quality solution immediately contributes to the evolutionary search without waiting for the completion of an entire generation. This strategy accelerates convergence while maintaining population diversity through continuous elite preservation.

The optimization process terminates when one of the predefined stopping criteria is satisfied. In this study, termination occurs when either the maximum number of evaluations is reached or the Reserved Elite Population exhibits no further improvement for a predefined number of consecutive evaluations. The best chromosome stored in the Reserved Elite Population is then selected as the optimal CNN channel mask and subsequently employed during the final classification stage.

3. Experimental Setup

The proposed framework was implemented in Python using the Google Colaboratory cloud computing platform. The proposed framework was evaluated using the publicly available Brain Tumor MRI dataset developed by Masoud Nickparvar. The dataset consists of four clinically relevant categories:

- Glioma
- Meningioma
- Pituitary Tumor
- No Tumor

The complete dataset contains 7,023 T1-weighted contrast-enhanced magnetic resonance imaging (MRI) images collected from different patients. The images are organized into independent training subset contains 5,712 images and testing subsets contains 1,311 images. The preprocessing pipeline consisted of the following steps:

1. Reading the original MRI image.
2. Converting the image into RGB format when necessary.
3. Resizing every image to **224** × **224** pixels.
4. Converting pixel values into floating-point representation.
5. Applying the standard ResNet50 preprocessing to normalize the input according to the ImageNet training distribution.

The parameters of Hasan's Online Genetic Algorithm are summarized in Table I.

Table I. Configuration of Hasan's Online Genetic Algorithm

Parameter	Value
Population Size	30
Reserved Elite Population (REP)	10
Tournament Size	4
Crossover Probability	0.90
Initial Mutation Rate	0.18
Minimum Mutation Rate	0.08
Mutation Decay	0.95
Gaussian Mutation Sigma	0.10
Maximum Generations	20
Maximum Evaluations	600
REP Stagnation Limit	40

The classification performance was measured using the following metrics: Accuracy, Precision, Recall, and F1-score.

4. Experimental Results and Discussion

The simulation results show that the maximum fitness is increasing rapidly at the beginning of the evaluations which demonstrates that the exploration of the search space is effective as seen in figure 5 which shows the process of the evolution of the fitness value. One can easily see that after a point the fitness value becomes more stable which indicates that the evolutionary search is converging towards the best channel subset.

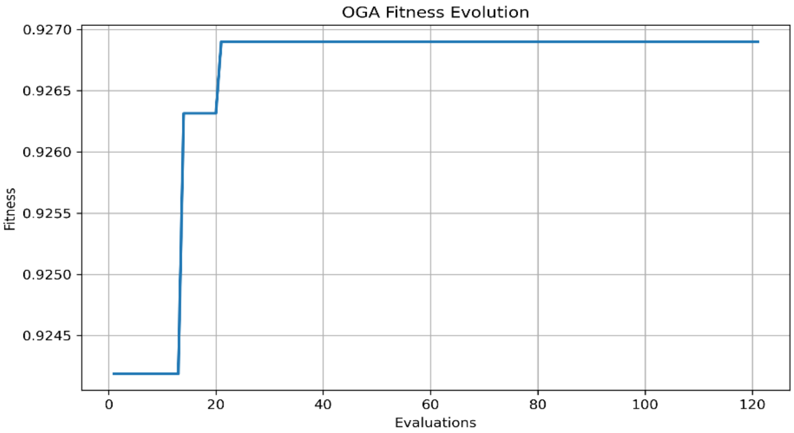

Figure 5 (a). OGA fitness convergence

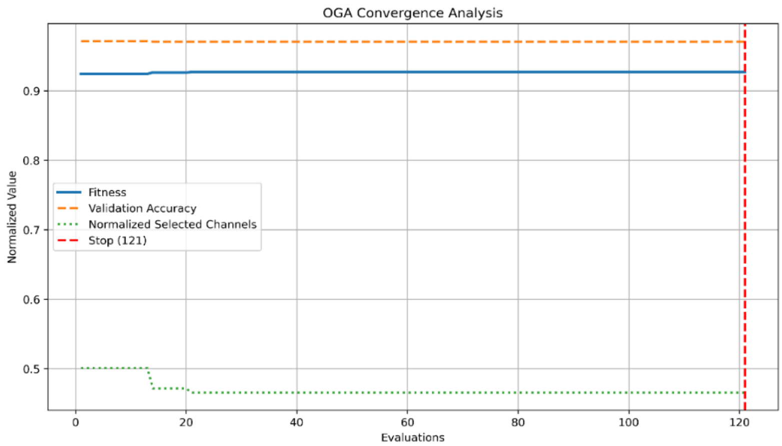

Figure 5 (b). OGA convergence analysis

The optimization process allows improving the classification performance until some stable state is reached. And from this, it can be stated that the OGA is able to select more and more informative metric channel combinations without the necessity to change or retrain the basic CNN structure. shown in Figure 6.

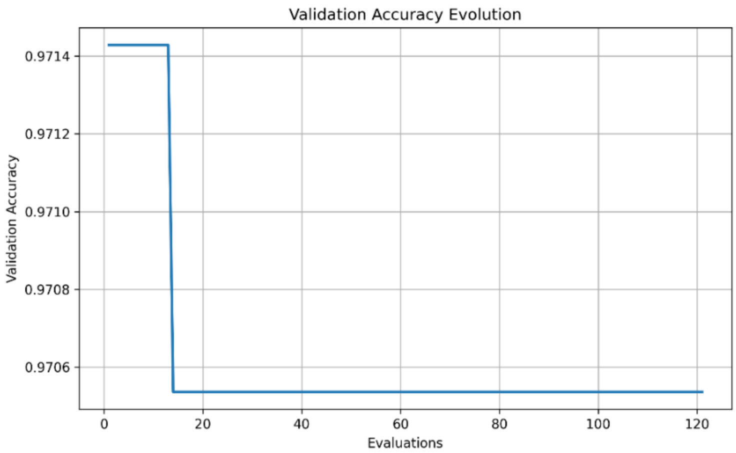

Figure 6. OGA validation accuracy

Throughout the optimization process, the populations gradually converge to compact representations of channels with better discrimination. This illustrates that the proposed Online Genetic Algorithm has the capability to enhance the efficiency of representation as well as its classification ability. Figure 7 shows the trend in the number of chosen channels.

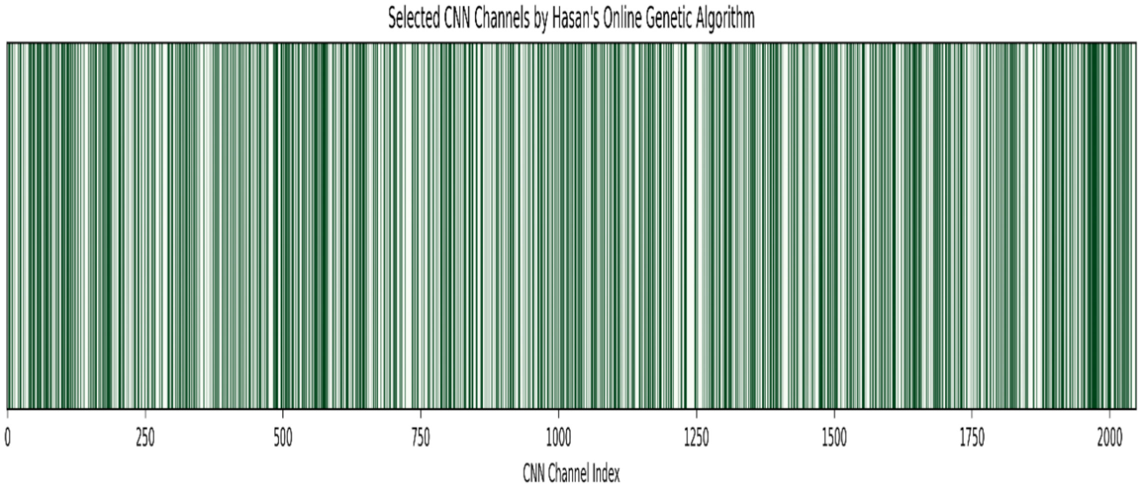

Figure 7. Channel selection

The online optimization the elite matrix of individuals is updated whenever a new set of channels appears. This will result in keeping the population at competitive positions during the search and decreasing the chance for falling into local hills and operate the GA. Figure 8 illustrates the process of reserving elite population members.

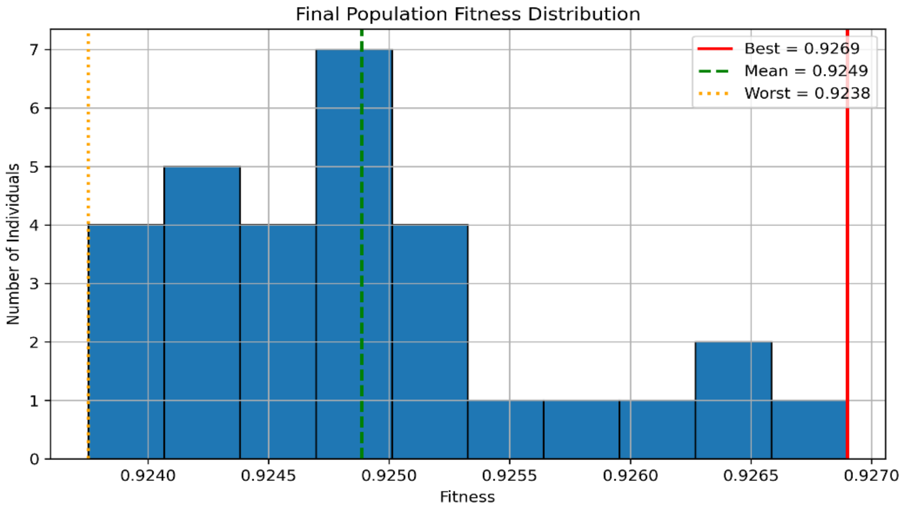

Figure 8. REP fitness distribution

The final result of this process is that the best individual achieved a fitness measure of 0.9269, which corresponding to 97.05% classification rate on the test data. After finishing the evolutionary optimization, the best individual from Reserved Elite Population was selected and became the channel-selection mask. This mask contained 954 Informative channels out of 2048 originally extracted from data by pre-trained ResNet50. corresponding to a channel reduction of approximately **53.42%**. as shown in figure 9.

The optimized channel representation was then used to train the Support Vector Machine (SVM), which was evaluated using the independent testing dataset.

Table III shows a summary of the outcomes in terms of classification performance with the means of the optimized channel representation technique. the proposed system had an accuracy rate of 93.19% which means that they were able to eliminate more than halve of original number of CNN channels while still being effective in terms of prediction accuracy. The precision, recall, and F1-scores were found to be 93.82%, 93.19%, and 92.98%, respectively.

Table 3. Classification Performance of the Proposed Framework

Metric	Value
Accuracy	93.19%
Precision	93.82%
Recall	93.19%
F1-score	92.98%
Original Channels	2048
Selected Channels	954
Channel Reduction	53.42%

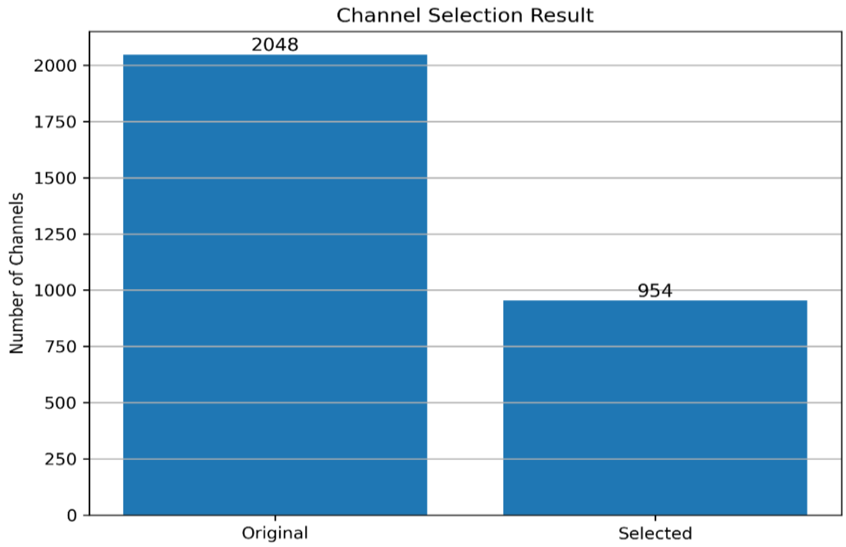

Figure 9. Channel reduction

Figure 10 shows a confusion matrix that illustrates the classifier predictions for the various tumor categories. The confusion matrix showed that most of the observations were assigned to the correct class, indicating that a good representation of the channels preserved the information learned by the CNN that was trained before. The best performance was noticed for the pituitary tumor and no tumor categories and maximum confusion was found between glioma and meningioma classes.

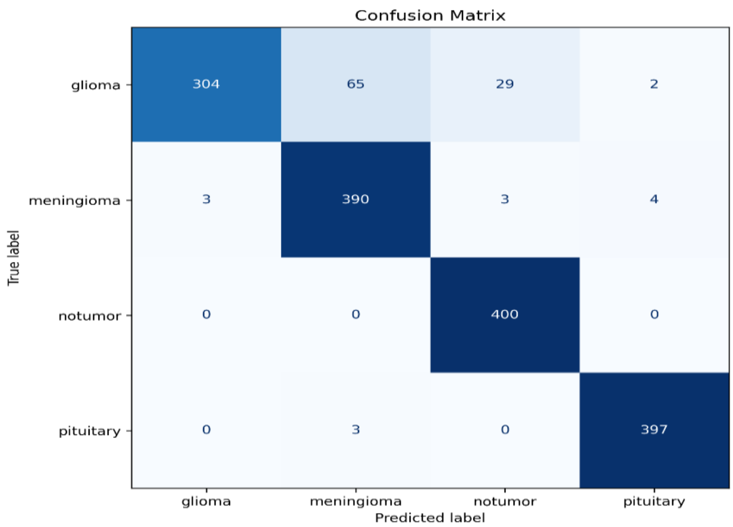

Figure 10. confusion matrix

The detailed classification results illustrate that the evaluation metrics remained relatively high across the four classes. The weighted precision of 93.82% indicates that there are few false positive predictions and the weighted recall of 93.19% signifies that the majority of the tested samples were correctly classified. In addition, the F1-score of 92.98% is indicative of a good trade-off between precision and recall, thus showing that the selected subset of the channels retained enough discriminative power.

6. Conclusion

In this paper, an evolutionary CNN channel selection method based on Hasan's Online Genetic Algorithm (OGA) used for optimizing deep convolutional neural network's. Our proposed method does not change the CNN architecture via pruning of its channels, retraining, or optimizing hyperparameters; it rather defines the process of channel selection as a problem of binary optimization and performs the work at the level of features that have been extracted from CNN. The proposed method allows for efficiently reducing the number of channels without any deterioration of the quality of classification carried out by the CNN.

The proposed method has been validated through the example of multiclass brain tumor MRI classification. Experimental results showed that Hasan's Online Genetic Algorithm has allowed us to reduce the number of original 2048 channels used by the ResNet50 CNN to only 954 channels which have provided this particular dimension of the CNN with the discriminatory power sufficient for successful classification of images.

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