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An Intelligent Grading of Astrocytomas Brain Tumors Through Improved Harish Hawks Optimized Deep CNN

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***Abstract*— Brain cancer continues to be among the leading causes of death for both men and women and much effort have been expended in the form of screening programs for prevention. Given the exponential growth in the number of MRI collected by these programs, computer-assisted diagnosis has become a necessity. Computer-assisted detection techniques developed to date to improve diagnosis without multiple systematic readings have not resulted in a significant improvement in performance measures. In this context, the use of automatic image processing techniques resulting from deep learning represents a promising avenue for assisting in the diagnosis of brain cancer. In this paper, present a deep learning approach based on a Convolutional Neural Network (CNN) model for brain tumor classification. The proposed approach aims to classify the brain tumors in to different grades. Experimental results on MRI images using the BRATS dataset show that the HHO-CNN model achieved high processing performances with 97% of accuracy in the proposed classification task when compared with other classification techniques and state-of-the-art models.)**

Keywords—Astrocytoma, MRI, IHHO, CNN

I. INTRODUCTION

The advancement in medical technologies helps the clinical experts to facilitate more efficient e-health care systems to the patients. There is a number of medical domains where e-health care systems are beneficial [1]. Computer vision-based applications of biomedical imaging are gaining more importance as they provide recognition information to the radiologist for batter treatment-related problems. Different medical imaging techniques and methods that include X-ray, Magnetic Resonance Imaging (MRIs), Ultrasound, and Computed Tomography (CT), have a great influence on the diagnosis and treatment process of patients. The formation of abnormal groups of cells inside the brain or near it leads to the initialization of a brain tumor. These abnormal cells affect the health of the patient and abrupt the processing of the brain [2]. The most common type of brain tumor known as Astrocytoma arises from the astrocyte cells, which form part of the brain's supportive (neuroglial) tissue. An astrocytoma develops from star-shaped glial cells (astrocytes) that support nerve cells. These tumors can be located anywhere in the brain, but the most common location is in the frontal lobe. Astrocytoma’s are the most common primary CNS tumor. The physician, usually the neurosurgeon or neuro-oncologist, will discuss the type and location of an astrocytoma. The pathologist will assign it a grade. Astrocytoma’s are generally classified as low or high grade. Low-grade astrocytoma’s are slow growing. High-grade astrocytoma’s (grades three and four) grow more quickly. The characteristics of an astrocytoma vary depending on the tumor’s grade and location. Most people are functioning normally when diagnosed with a low-grade astrocytoma [3-5]. Symptoms tend to be subtle and may take one to two years to diagnose. This is because the brain can often adapt to a slow-growing tumor for a period of time. High-grade tumors may present with changes that are sudden and dramatic. Brain imaging analysis, diagnosis, and treatment with adopted medical imaging techniques are the main focus of research for the researcher, radiologist and clinical experts. A variety of image-processing techniques and methods have been used for the diagnosis and treatment of a brain tumor. The development of new technologies, especially artificial intelligence and machine learning, has had a significant impact on medical field, providing an important support tool for many medical branches, including imaging. Different machine-learning methods for image segmentation and classification are applied in MRI image processing to provide radiologists with a second opinion. In the field of computational medical imaging, methods of deep convolutional neural networks (CNN) [6] have proved successful for the hierarchical unsupervised learning of imaging features of increasingly complex data directly from raw images, allowing discovering the relevant characteristics, instead of extracting features defined a priori by the user. The remainder of this paper is divided into four sections. After introducing, related works on brain cancer classification are reviewed in Section 2. Section 3 presents the proposed HHO based CNN model for brain tumor classification. Experiments, results and comparison with popular CNNs models are detailed in Section 4. Finally, this paper is concluded in Section 5.

II .RELATED WORKS

Research related to the detection of brain cancer has increased during the last decade. Much work has been directed towards the detection of the presence of cancerous tissue in the brain and the classification of tumors. Some researchers have preferred to design aided diagnosis systems based on Content based image retrieval techniques that would have the advantage of offering radiologists images available in a medical image database, whose content is known and which would be similar to image request for which the radiologist would have doubts. However, this approach also raises problems of search time and adequate similarity measurement between the request image and those contained in the database.

S. Chaplot et al. [7] proposed a novel strategy for the classification of magnetic resource images of human brain which utilizes wavelets as contribution to support vector machine and neural system self-organizing maps. The proposed technique orders MR brain images as abnormal or normal. Their proposed approach has a dataset of 52 MR brain images. A rate of over 94% was achieved with the self-organizing maps (SOM) whereas and 98% using the support vector machine method. It was observed that the classification rate is high for a support vector machine classifier if compared with a self-organizing map-based approach.

M. Maitra et al. [8] proposed new approach for mechanized diagnosis, for the classification of MRI images. The proposed strategy is seemingly a variant of orthogonal discrete wavelet transform (DWT), called Slantlet transform for highlight extraction. Here, a 2-D MR picture processes its intensity histogram and then connected to Slantlet transform as its histogram flag.

Y. Zhang et al. [9] proposed a hybrid technique in light of forward neural network (FNN) to group MR brain images. The proposed strategy initially utilized the discrete wavelet transform in order to extract main features from MR Images and after that applied the principal component analysis technique to diminish feature space to a limit. The diminished components were sent to a forward neural network (FNN), where the parameters were upgraded utilizing an improved artificial bee colony algorithm (ABC) calculation in view of both fitness scaling and chaotic theory.

The segmentation of the brain tumor was deliberated by Iqbal et al. [13] in the multi-spectral MR pictures with the support of convolutional neural networks. The current inspection provides a practical system manner for the brain tumor separation through the multi-modular pictures.

Sharif et al. [14] presented an active deep learning system for the segmentation and classification of brain tumors. They initially performed contrast enhancement, and the resultant image was passed to the Saliency-based Deep Learning (SbDL) method, for the construction of a saliency map. The thresholding was applied in the next step, and the resultant images were used to fine-tune the pre-trained CNN model Inception V3. They used BRATS 2015, 2017, and 2018 datasets for evaluation, and achieved improved classification accuracy. Other methods were also introduced in the literature for brain tumour classification, such as a generative adversarial network artificial neural network (ANN)-based learning [15], ELM-based learning [16], residual network [17], standard-features-based classification [18,19], adaptive independent subspace analysis [20], transfer learning-based tumours classification [21], and Excitation DNN [22]. Deep learning refers to advanced statistical learning methods organized in multiple layers, to extract representations of data on multiple levels, and whose layers are not predefined by the user but learned directly from the data by the algorithm, thus mimicking human neuronal functioning [10]. It has been successfully applied to various pathologies and modalities, including the use of convolutional networks (CNN) that exploit large databases for the extraction of relevant descriptors and segmentation [11]. The main challenge of cancer automatic aided diagnosis systems is dealing with the inherent complexity of MRI images. To deal with this, choose to use a powerful HHO based convolutional neural network of multiclass classification problem. Here use the ResNet model [12], one of state of the art in the image recognition competition ImageNet [13]. The ResNet is built for natural images processing but modified it to deal with MRI images for brain cancer classification using transfer learning.

Summarizing, with this survey we propose the following novel ideas.

- *A new technique in which A second order convolutional filter-based CNN is used for grade classification*
- *A novel method of Improved HHO based on EOBL technique is used for weight updating for time optimized Convergence.*
- *Using modified HHO-based 2nd order-CNN classifier to build an automated system for classifying different grades of brain tumor in MR Images.*
- *To determine the optimal subset of texture features to improve the accuracy of the classification and to create a classification system based on texture features that integrates HHO-based SVM and HHO-based Bag of visual terms.*
- *For various brain tumor classes, quantitative analysis is performed. Validate the accuracy of the classification of the proposed classifier and compare it with the current algorithms and the other two developed classifiers.*

III. PROPOSED CNN MODEL FOR MULTI-CLASS BRAIN CANCER CLASSIFICATION

The CNN model structure is simpler and easier to expand than the neurocognitive machine. In the neurocognitive machine, the down sampling layer and the convolutional layer alternate to form the function of feature extraction and abstraction, while in the convolutional neural network, the convolutional layer and the down sampling layer alternate, and their functions are similar. The convolution operation simplifies feature extraction, the excitation function replaces multiple nonlinear functions of the neurocognitive machine, and the pooling operation is also simpler [23]. The CNN architecture is shown in Figure 1.

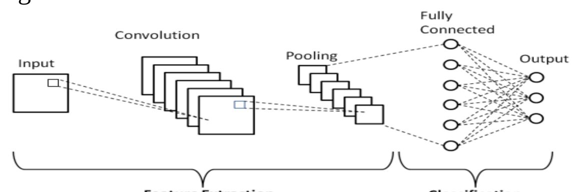


Figure 1: CNN architecture

A CNN is composed of several kinds of layers:

- Convolutional layer: creates a feature map to predict the class probabilities for each feature by applying a filter that scans the whole image, few pixels at a time.
- Pooling layer (down sampling): scales down the amount of information the convolutional layer generated for each feature and maintains the most essential information (the process of the convolutional and pooling layers usually repeats several times).
- Fully connected input layer: “flattens” the outputs generated by previous layers to turn them into a single vector that can be used as an input for the next layer.
- Fully connected layer: applies weights over the input generated by the feature analysis to predict an accurate label.
- Fully connected output layer: generates the final probabilities to determine a class for the image.

The convolutional layer is composed of a set of convolutional kernels where each neuron acts as a kernel. However, if the kernel is symmetric, the convolution operation becomes a correlation operation. Convolutional kernel works by dividing the image into small slices, commonly known as receptive fields [25]. Convolution operation can be expressed as follows:

$$f_1^k(p,q) = \sum_c \sum_{x,y} i_c(x,y) \,.\, e_1^k(u,v) \qquad (1)$$

Here $i_c(x,y)$ is theoretically calculated by finding the square root of the average value of the squared sum of 8-point nearest neighbor of imputed MRI image pixel’s within the ROI.

Where, $i_c(x,y)$is an element of the input image tensor I_c , which is element wise multiplied by $e_1^k(u,v)$ index of the kth convolutional kernel k_1 of the lth layer. Whereas output feature-map of the kth convolutional operation can be expressed as $F_1^k = [f_1^k(1,1), \ldots (f_1^k(p,q), \ldots f_1^k(P,Q))]$.

In pooling layer once features are extracted, its exact location becomes less important as long as its approximate position relative to others is preserved. Pooling or down-sampling is an interesting local operation. It sums up similar information in the neighborhood of the receptive field and outputs the dominant response within this local region

$$Z_l^k = g_p\left(F_l^k\right) \qquad (2)$$

Equation (2) shows the pooling operation in which Z_l^k represents the pooled feature-map of l^{th} layer for k^{th} input feature-map F_l^k , whereas g_p (.) defines the type of pooling operation. The use of pooling operation helps to extract a combination of features, which are invariant to translational shifts and small distortions. The activation function for a convolved feature-map is defined in equation (3).

$$T_l^k = g_a(F_l^k) \qquad (3)$$

The above equation F_l^k is an output of a convolution, which is assigned to activation function g_a (.) that adds non-linearity and returns a transformed output T_l^k for lth layer.

Batch normalization is used to address the issues related to the internal covariance shift within feature-maps. The internal covariance shift is a change in the distribution of hidden units' values, which slows down the convergence (by forcing learning rate to small value) and requires careful initialization of parameters. Batch normalization for a transformed feature-map F_l^k is shown in equation (4).

$$N_l^k = \frac{F_l^k - \mu_B}{\sqrt{\sigma_B^2 + \varepsilon}} \qquad (4)$$

In equation (4), N_l^k represents normalized depict mean andμ_B and σ_B^2feature-map, F_l^k is the input feature-map, B variance of a feature-map for a mini batch respectively. Dropout introduces regularization within the network, which ultimately improves generalization by randomly skipping some units or connections with a certain probability.

IV.RESNET50

ResNet50 is a 50-layer Residual Network with 26M parameters. The residual network is a deep convolutional neural network model that is introduced by Microsoft in 2015 [26]. In Residual network rather than learning features, we learn from residuals that are subtraction of features learned from the layer's inputs.

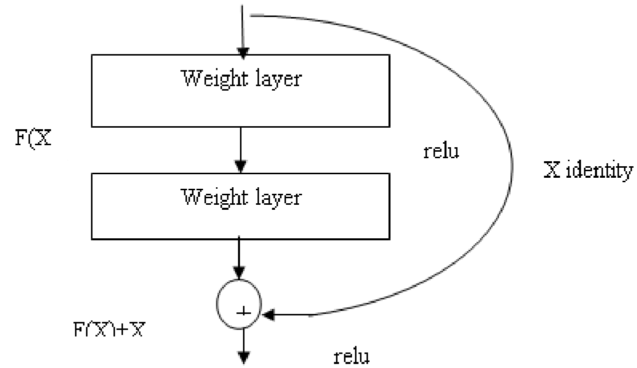


Figure 2: Residual learning building blocks

ResNet used the skip connection to propagate information across layers. ResNet connects nth layer input directly to some (n+x)th layer which enables additional layers to be stacked and a to establish a deep network. We used a pre-trained ResNet50 model in our experiment and fine-tuned it. In Figure 2, the architecture of ResNet50 is shown.

The model has flattened layer, which is followed by densely connected neurons. Some of the perceptron has been dropped off in order to prevent overfitting. The loss function utilized the "binary cross entropy" whereas the optimiser is HHO. In deep neural networks, apply different optimization methods by adjusting parameters such as weights and learning rates to reduce the loss. Here used the Harish Hawks Optimizer (HHO), proposed by Heidari et al. in 2019 [20]. The proposed block diagram of HHO based CNN is shown in figure 3.

V.HARRIS HAWKS OPTIMIZATION

Harris Hawks Optimization (HHO) is a novel nature-inspired, gradient-free, and population-based optimization algorithm that imitates the chasing style of Harris Hawks' birds. HHO was introduced recently by Heidari et al. in 2019 [27]. The algorithm follows the attacking behaviours' of Harris hawks on the prey in nature, such as preaching, predation, and surprise pounce strategies. Like other meta-heuristic algorithms, HHO includes two main phases: exploration and exploitation, However, HHO has two stages for exploration and four for exploitation, which described in detail as follows.

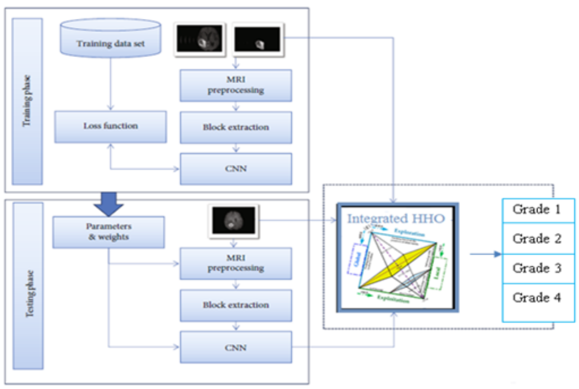


Figure 3: proposed HHO based CNN

Initialization Phase: In this phase, the objective function and its solution space are defined. In addition, the values for the parameters are assigned, and the initial population is created. Exploration Phase: It is the phase where Harris Hawks search for the prey (the rabbit). The hawks have compelling eyes that can help them to detect and track the prey, but it is sometimes difficult to see the prey. In this case, the hawks wait and monitor the site hoping to observe the prey. Practically, in each iteration all Harris hawks are the candidate solutions, and the fitness value is calculated for each of them based on the intended prey. After that, the Harris hawks may wait in some positions to detect the prey based on the following equation

$$X(t+1) = \begin{cases} X_{rand}(t) - r_1|X_{rand}(t) - 2r_2X(t)| & q \geq 0.5 \\ (X_{rabbit}(t) - X_m(t)) - r_3\big(LB + r_4(UB - LB)\big) & q < 0.5 \end{cases} \quad (5)$$

Where $X(t+1)$ is the position of hawks in the next iteration t, $X_{rabbit}(t)$ is the rabbit position, $X(t)$is the current position vector of the hawks, $X_m(t)$ refers to the average position of the current population of hawks. The variables r_1, r_2, r_3, r_4, and q (wait) are random numbers over the interval [0, 1], and LB and UB represent the upper and lower bounds of the problem variables. HHO uses a straightforward way to calculate the average position of hawks $X_m(t)$using the following equation

$$X_m(t) = \frac{1}{N}\sum_{i=1}^{N} X_i(t) \qquad (6)$$

where $X_i(t)$ refers to the position of the hawks in iteration t; and N represents the total number of hawks.

Transition From Exploration to Exploitation: It is critical to the performance of meta-heuristic algorithms to maintain the right balance between exploration and exploitation. In HHO, shifting between the exploration phase and exploitation phase, and between different exploitations depend on the prey escaping energy (E). HHO assumes that the energy of the rabbit is reducing during escaping from the hawks, which can be calculated as follows

$$E = E_0\left(1 - \frac{t}{T}\right) \qquad (7)$$

Where E is escaping energy, E_0 is the initial state of energy which its value randomly changes over the interval (-1, 1), and T is the maximum number of iterations. When the escaping energy of the rabbit $|E\,| \geq 1$, HHO redirects the hawks to explore different regions searching for the rabbit (exploration phase). However, when its energy is reduced$|E\,| < 1$, the hawks search the neighborhood for the solution during the exploitation phase.

Exploitation Phase: In this phase, Harris hawks attack the prey based on the position detected in the previous phase. However, the rabbit always attempts to escape, and the hawks follow the chasing strategy. Hence, HHO is designed based on four possible strategies of attacking techniques. Two variables indicate which strategy will be performed, r and$|E\,|$. While $|E\,|$ is the escaping energy of the rabbit, r refers to the probability of escaping, where r < 0:5 indicate a higher chance for the rabbit to escape successfully and $r \geq$ 0: 5 for failure to escape.

The EOBL technique is used to improve the global search ability of HHO. The opposition point is defined as follows: for the individual $X_{\,i} = (x_{i;1};\, x_{i;2};\, \dots\, ;\, x_{i;D})$ in the current population $X_{\,e} = (x_{e;1};\, x_{e;2};\, \dots\, ;\, x_{e;D})$, then the elite opposite point $\breve{X}_{\,i} = (\breve{x}_{i;1};\, \breve{x}_{i;2};\, \dots\, ;\, \breve{x}_{i;D}))$ can be mathematically modeled as

$$\breve{x}_{i;j} = s \times \left(da_j + db_j\right) - x_{i,j} \qquad (8)$$

where $s \in [a_i, b_i], S \in U[0,1]$ S is a generalized factor. da_j and db_j are dynamic boundaries, which can be defined as

$$da_j = \min\left(x_{i;j}\right), \qquad db_j = \max\,(x_{i;j}) \qquad (9)$$

However, the corresponding opposite can exceed the search boundary $[\,a_i, b_i\,]$. To solve this matter, the transformed individual is assigned a random value within $[a_i, b_i]$as follows

$$\breve{x}_{i;j} = rand\left(a_j, b_j\right), \qquad if\,\breve{x}_{i;j} < a_j||\breve{x}_{i;j} > b_j \qquad (10)$$

HHO relies on the rabbit energy $|E\,|$ to shift from exploration to exploitation and to choose the current type of exploitation. It also uses the rabbit energy to prevent the hawks from falling in local optima.

VI.EXPERIMENTAL RESULTS AND ANALYSIS

- **Experimental Setup**

The proposed method has been implemented using the Matlab environment on Core 2 Duo, processor speed 1.6 GHz. The proposed system has been tested on the data set available at web [17]. The proposed system has been tested on the BRATS 2017 dataset with the size of "512 × 512" here 400 images are collected (4 sorts of evaluations) and each evaluation contains 100 images. It has also been tested on dataset of real brain MR images consisting of different grades of brain images.

- ***Confusion Matrix and Validation Metrics***

Confusion chart creates a confusion matrix chart from true labels true Labels and predicted labels predicted Labels and returns a Confusion Matrix Chart object. The rows of the confusion matrix correspond to the true class and the columns correspond to the predicted class. Diagonal and off-diagonal cells correspond to correctly and incorrectly classified observations, respectively. The performance of the classification model is often described by 'confusion matrix'. The elements of confusion matrix are as follows

- True Positives (TP): No. of Benign/ Malignant MR images those are classified as they are Benign/ Malignant.
- True Negatives (TN): No. of Non-Benign/ Non-Malignant MR images those are classified as they are Non-Benign/ Non-Malignant.
- False Positives (FP): No. of Non-Benign/ Non-Malignant images those are classified as they are Benign/ Malignant.
- False Negatives (TN): No. of Benign/ Malignant MR images those are classified as they are Non-Benign/ Non-Malignant

Here the validation metrics such as sensitivity, specificity, accuracy, precision and F- measure are evaluated.

Performance of classification phase

Here two different classifiers are used such as SVM and BOVW classifier. Support vector machine (SVM) is one of the techniques used for the classification purpose. BOVW classifier's main purpose is to reduce the time consumption; this classifier will automatically select the features that accompany this classification. Here this both classifiers, apply Harish Hawks Optimizer (HHO) methods by adjusting parameters such as weights and learning rates to reduce the loss. Table 1 shows the results of all experimentations.

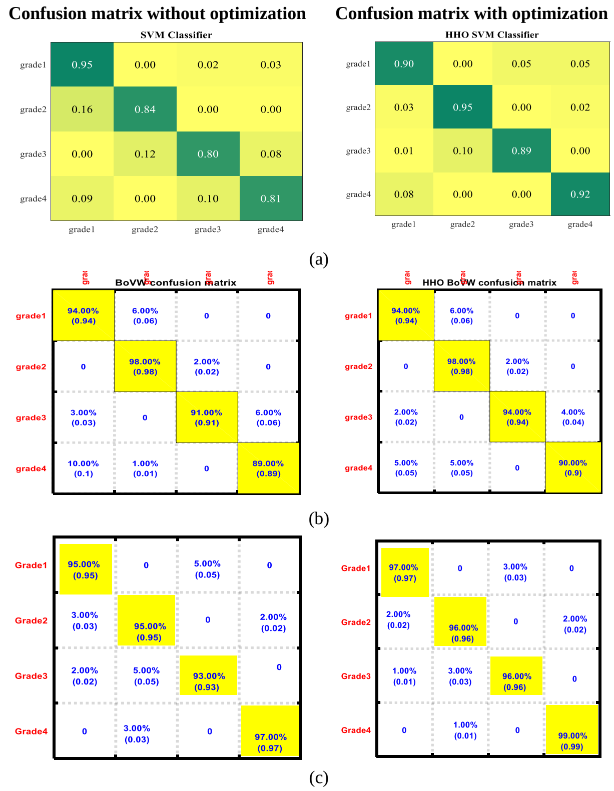


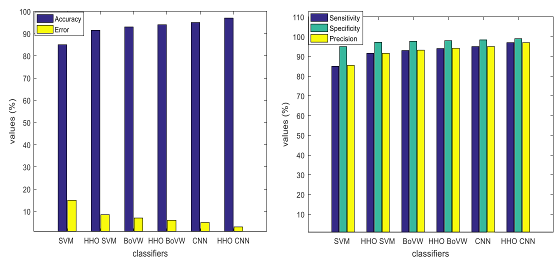
Figure 4: (a-c) confusion matrix of proposed Classifiers

Figure 4 shows the confusion matrix of SVM, BOVW and CNN classifiers with and without optimization in which classifiers classify the brain images based on the tetrolate and GL CM features.

Table 1: performance value of classifiers

Metrics	*SVM*	*HHO-SVM*	*BOVW*	*HHO-BOVW*	*CNN*	*HHO-CNN*
Accuracy	0.8500	0.9150	0.93000	0.9400	0.95	0.97
Error	0.1500	0.0850	0.0700	0.0600	0.05	0.03
Sensitivity	0.8500	0.9150	0.9300	0.9400	0.95	0.97
Specificity	0.9500	0.9717	0.9767	0.9800	0.9833	0.99
Precision	0.8542	0.9158	0.9318	0.9416	0.95027	0.9699
F1-Score	0.8495	0.9150	0.9300	0.9400	0.95005	0.96997

Figure 5 shows the Accuracy, Error, Sensitivity, Specificity and Precision plot of proposed classifiers. From the bar chart the HHO based CNN classifiers obtains higher accuracy, sensitivity, precision and specificity; the error value is lower than the proposed classifiers, the outcomes prove that the performance the proposed algorithm is excellent. The application of the proposed method for early detection of tumor is demonstrated to improve efficiency and accuracy of clinical practice. The application of the proposed method for tracking tumor is demonstrated to help pathologists distinguish exactly tumor region and its type of tumor.



(a) (b)

Figure 5: (a & b) comparison plot of various classifiers

VII. CONCLUSION AND FUTURE WORK

In the context of classification, deep convolutional neural networks (CNNs) have been widely proven in the scientific and industrial community. Here, investigated the performance of a deep neural network model on a classification task related to brain cancer detection. The modification applied to the ResNet-50 model proves that deep learning model used in natural images processing can achieves high performance in medical images processing. In our case we achieve about 97% of accuracy in the optimized brain tumor classification task and that outperform human expert in the diagnostic domain. The performance achieved can be improved if we provide more data using larger datasets. In this work an efficient methodology which combines the HHO with the Convolutional Neural Network (CNN) to classify the brain MRIs into different grades of Astrocytoma. In addition, using this classifier shows high accuracy compared to traditional classifiers. To further boost the model efficiency, different architecture and comprehensive hyper-parameter tuning technique can be conceived.

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