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Original Article

AlexNet – Adaptive Whale Optimization – Multi-class Support Vector Machine model for Brain Tumour Classification

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Abstract **-** *The brain tumor classification model assists doctors in deciding on the treatment of cancer. Various deep learning models for brain tumor classification are applied to improve classification accuracy. The existing models suffer from the limitation of overfitting problems in the classification. This research proposed the AlexNet – Adaptive Whale Optimization Algorithm (AWOA) – Multi-Class Support Vector Machine (MSVM) model for brain tumor classification. The AWOA method increases the exploration and exploitation that helps select features for classification. The AlexNet model consists of 8 layer that provides effective feature extraction from the input dataset. The augmentation method helps to handle the imbalanced data problem in classification due to data generation. The AlexNet – AWOA – MSVM achieves an accuracy of 99.92 %, and WOA-RBNN has 96 % accuracy in brain tumor classification.*

Keywords - *Adaptive Whale Optimization Algorithm, AlexNet, Augmentation, Brain tumor classification, Multi-Class Support Vector Machine.*

1. Introduction

Medical image classification and automatic segmentation play an important role in treating brain tumors, growth prediction, and diagnosis. Early diagnosis of brain tumors provides a faster response in treatment that increases the survival rate of patients. Brain tumor classification and location in large medical image databases on manual process requires high cost in terms of time and effort. Therefore, automatic detection of classification and location is highly required in the medical field [1]. Accurate segmentation is achieved using Automatic detection techniques and classifying the brain tumor in MRI images, so doctors provide efficient treatments for patients [2]. The performance of the deep learning technology depends on the annotated dataset size, and this is challenging to label many medical images based on the volume and complexity of medical data [3]. Brain tumor manual segmentation is error-prone and more time-consuming. Early and accurate tumor detection assists in expert intervention in inpatient evaluation [4]. Automatic and semi-automatic segmentation of brain tumors provides efficient detection and accurate segmentation of abnormal brain regions for many patients [5].

Pathological examinations of imaging modalities are Computed Tomography (CT) or Magnetic Resonance Imaging (MRI) interpretation, and clinical examination is carried out in the final diagnosis [6]. Pituitary and Meningioma tumors easily diagnose the occurrence location, but Gliomas are difficult to analyze. Deep learning is a machine learning subset that can evaluate multiple data representation levels for detection and prediction tasks. Convolutional Neural Networks (CNN) is a deep neural networks model that works efficiently on images and provides remarkable results in tasks of segmentation, object detection, and image classification [7, 8]. A CNN model acts as a combined unit and consists of a feature extractor and a classifier [9, 10]. The contribution of the paper is discussed as follows:

1. The augmentation method increases the data training for minority classes in the datasets. The alexnet model is applied for feature extraction that provides an effective feature extraction process.
2. AWOA method is applied with initialization of the search near the high fitness value of the whale to increase the exploitation. AWOA method is applied to increase the exploration and exploitation of the search.
3. The AWOA selected features are applied to the MSVM model for brain tumor classification. MSVM model can handle the high dimensional data and increases the classification performance.

The paper is organized as follows: recent research in brain tumor classification is given in Section 2, and the Alexnet – AWOA – MSVM model is explained in Section 3. The implementation details are in Section 4, and the results are explained in Section 5. The conclusion of this research paper is given in Section 6.

2. Literature Review

in medical imaging, multi-class brain tumor classification is an important research field. Recent research in the classification of brain tumors was reviewed with its advantages and limitations.

Sharif et al. [11] applied a pre-trained Densenet201 model with fine-tuning and deep transfer learning for the imbalance dataset to classify brain tumors. The average pool layer was used to extract the features in the trained model, and each tumor information was represented with deep information. Metaheuristic Genetic algorithm and Entropy Kurtosis based features were applied in the developed model. The threshold function was applied to refine the GA-selected features for classification. Features were fused using a non-redundant serial-based method, and a multi-class SVM cubic classifier was used for classification. The model performance in brain tumor classification was evaluated using BRATS2018 and BRATS2019 datasets. The GA-based model has lower convergence, the SVM cubic classifier has an imbalanced data problem, and the Densenet201 model has an overfitting problem.

Kumar et al. [12] applied ResNet50, and global average pooling was applied to solve the vanishing gradient problem and overfitting problem in classifying brain tumors. Flatten layer was applied to convert the multi-dimensional features into a one-dimensional feature vector. Three tumors of CT-MRI images were used to evaluate the ResNet50 model in brain tumor classification. The stochastic gradient descent method is applied in the ResNet50 model for model optimization. The model shows higher performance with data augmentation in brain tumor classification. The overfitting in training the ResNet50 model degrades the classification performance.

Bodapati et al. [13] applied a two-channel deep neural network for tumor classification. The pooling-based technique was proposed in Xception and InceptionResNetV2 network convolutional blocks extract the local feature representations. an attention method was applied to focus highly on the images' tumor regions for classification. The two sets of tumor representation were jointly trained in the two-channel model end-to-end to provide good generalization. The developed model was tested using Figshare and BRATS2018 datasets to evaluate the performance. The developed model avoids pre-processing, augmentation techniques, and fine-tuning for classification. The model has higher efficiency in both datasets in tumor classification.

Alhassan et al. [14] applied histogram oriented gradient and normalization technique to improve the visible level of brain images, and normalized brain images were used to extract the features. The histogram descriptor provides the edges of the image, and contour features provide other feature descriptors. CNN model was applied with extracted features to classify pituitary, glioma, and meningiomas classes. The RELU activation features of the hard switch were applied in the CNN model to improve the efficiency of classification performance. The CNN-based model provides higher efficiency than the deep learning model with fine-tuning and transfers learning.

Dixit and Nanda [15] applied an improved Whale Optimization Algorithm (WOA) in Radial Basis Neural Network (RBNN) to predict optimal cluster center, accuracy, and convergence speed in the classification of brain tumor. The fuzzy C Means (FCM) clustering method was applied for segmentation to identify the tumor region. The Principal Component Analysis (PCA) wavelet transform, entropy, and mean were applied for the feature extraction process. Feature vector was applied in RBNN layer, and improved WOA finds optimal cluster. The WOA-RBNN model performs the classification of tumors in input images. The FCM-WOA-RBNN model performance is evaluated on the BRATS2015 dataset.

3. Proposed Method

The proposed Alexnet – AWOA – MSVM model is evaluated using BRATS 2018, BRATS 2019, and CE-MRI datasets. The augmentation method is applied to increase the data in the minority class. The alexnet model is applied for the feature extraction process in input images. The AWOA method selects relevant features due to the exploration-exploitation process. The MSVM uses the selected features for classification. The flow of the Alexnet – AWOA – MSVM model is shown in Figure 1.

3.1. Augmentation

Regularization of data augmentation is applied to improve the generalization of the method, and deep learning models resolve the problem of overfitting to improve performance by training large data for efficient learners [12]. The Alexnet-AWOA-MSVM method exhibit the generalization property to train the model with augmented data. for model training, various orientations and rotation-based augmentation techniques are applied in medical images. Image rotation of 0°, 90°, 180°, and 270° augmentations were carried out, and 12,256 images were generated in total.

3.2. AlexNet feature extraction

The alexNet model provides efficient image classification performance superior to previous methods [16 - 18]. The activation function was the first improvement made in the model and applied to a neural network for effective analysis. The arctan, tanh, and logistic functions are traditional activation functions. Vanishing gradient problem is created in deep learning model due to large gradient value when input is near a value of 0. Rectified Linear Unit (ReLU) is applied, and the ReLU activation function is given in equation (1).

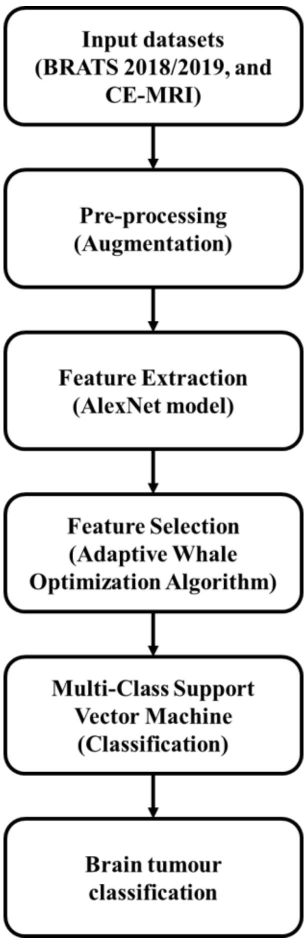

Fig. 1 The Alexnet - AWOA - MSVM model in classification

$$\mathrm{Re}\,LU(x) = \max(x, 0) \tag{1}$$

If the input is not less than 0, the ReLU gradient is set as 1. The ReLU in deep networks has faster convergence than the tanh unit, and this process accelerates the training process.

A part of neurons was trained in the dropout layer in every iteration. for instance, dropout is set as 50 %, then half of the values of the neurons are used for training. Dropout is applied for a neuron to cooperate with others to improve generalization and reduce joint adaptation between neurons. A certain extent of overfit occurs for each single sub-networks and shares the same loss function. The entire network output is the average of sub-networks. The robustness of the model is improved using the dropout layer.

Automatic feature extraction and reduction were carried out using a pooling and convolution layer. Convolution is given in equation (2) with an image M of size (m, n).

$$C(m,n) = (M \times w)(m,n) = \sum_k \sum_l M\left(m-k, n-1\right) w(k,l) \tag{2}$$

Where the (k,l) size of the convolution kernel is w, features are learned from the images using the convolution process, and model complexity is reduced by parameter sharing. Feature reduction is carried out in the pooling layer, feature map of a neighboring pixel group in pooling, and some strategy is used to generate a value. Every 2×2 block max value is generated in max pooling, and a 4×4 feature map is applied to reduce feature dimension.

Normalization of a cross channel in local normalization improves generalization. Normalized feature maps are applied to the next layers, and the normalization of the cross channel has several adjacent maps sum at the same position.

3.3. Adaptive Whale Optimization Algorithm (AWOA)

The WOA method [19, 20] consists of three phases: prey search, encircling prey, and bubble-net feeding.

3.3.1. Encircling prey

Prey location is identified by Humpback whales and encircle them. Target prey is the best search agent of WOA, and position updates are carried out using humpback whales as an agent of best search over the iteration process. The behavior in the mathematical form is given in equations (3, 4).

$$\vec{D} = \left|\vec{C} \times \vec{X}(t) - \vec{X}(t)\right| \tag{3}$$

$$\vec{X}(t+1) = \vec{X}(t) - \vec{A} \times \vec{D} \tag{4}$$

Where element-wise multiplication is denoted as ×, the coefficient vectors are $\vec{A}\, and\, \vec{B}$, the current iteration is denoted as t, and the best search agent position is denoted as $X^*(t)^2$. Equations (5, 6) are calculated using coefficient vectors $\vec{A}\, and\, \vec{C}$.

$$\vec{A} = 2\vec{a}.\vec{r} - \vec{a} \tag{5}$$

$$\vec{C} = 2 \times \vec{r} \tag{6}$$

Where the random vector $\vec{r}$ is in the range of [0, 1], exploration-exploitation phases and iterations linearly decrease $\vec{a}$ from 2 to 0. Update the control parameter ~ an as $\vec{a} = 2(1 - t / \mathrm{I}_{max})$, a maximum number of iterations, and iteration index are denoted as I_{max} t and, respectively.

Exploration and exploitation balance is denoted in equations (5) and (6). Both equations of perimeter r consider position updates of stochastic behavior. The random number range decreases from 2 to 0 in equation (5).

When $A \geq 1$ exploration is completed, exploitation is carried out by the WOA method $A < 1$. Permanently trapped probability in the local solution is reduced by exploitation, and the parameter C is in a random number. Optimization exploration and exploitation lead to boosting.

3.3.1. Bubble-Net Attacking Method

Spiral updating posting and shrinking encircling are simultaneously processed in the model for the bubble-net attacking method of humpback whales. The coefficient vector $\vec{A}$ in the [-1, 1] setting is achieved by shrinking, encircling, and reduc $\vec{a}$ ing the value in iterations. The location between the position of the best search and the current agent position is set as a new position.

Humpback whales of helix-shaped movement are mimicked for whale and prey location in the spiral equation, as in equations (7, 8).

$$D' = \left(\overrightarrow{X^*}(t) - \vec{X}(t)\right) \quad (7)$$

$$\vec{X}(t+1) = D'.e^{bl}.\cos(2\pi l) + \overrightarrow{X^*}(t) \quad (8)$$

Where the random number is in the range of [−1, 1], the logarithmic spiral shape of the constant is denoted as b .

Humpback whales surround prey without reducing the circle and process in spiral-shaped paths simultaneously. The spiral method and shrinking encircling methods are applied at the same time. Each method is performed at 50 % probability to model the behavior, as in equation (9).

$$\vec{X}(t+1) = \begin{cases} \overrightarrow{X^*}(t) - \vec{A}.\vec{D} & if\ p < 0.5 \\ \vec{D}'.e^{bl}.\cos(2\pi l) + \overrightarrow{X^*}(t) & if\ p \geq 0.5 \end{cases} \quad (9)$$

where p as a random number in [0, 1].

3.3.3. Prey Search

The shrinking encircling method is applied for prey search, coefficient vectors $\vec{A}$ $|A| > 1$ are used, and the best search agent position $\overrightarrow{X^*}(t)$ is replaced by $\overrightarrow{X_{rand}}$ a position to select the whale from the current population randomly. The global search increases the search space, and humpback whales are kept away from the random whale. The mathematical model of prey search is given in equations (10) and (11).

$$\vec{D} = \left|\vec{C}.\overrightarrow{X_{rand}} - \vec{X}(t)\right| \quad (10)$$

$$\vec{X}(t+1) = \overrightarrow{X_{rand}} - \vec{A}.\vec{D} \quad (11)$$

Equation (12) and (13) performs the search process for the last 50 iterations.

$$\vec{D} = \left|\vec{C}.D' - \vec{X}(t)\right| \quad (12)$$

$$\vec{X}(t+1) = D' - \vec{A}.\vec{D} \quad (13)$$

The bubble-net attacking method and prey search are two phases of a meta-heuristic method: exploration and exploitation. The bubble-net attacking method focuses on local region search using the current best solution exploitation, and prey search is applied to increase solution diversity to achieve a global solution. Exploitation is more desired as iterations increase, and exploration is applied at initial iterations. Many efforts are applied to improve the WOA method, which focuses on exploration and exploitation capability with their balance.

3.4. Multi-Class Support Vector Machine

Consider a vector $x_i \in R^p$ of features, p and class is denoted as $y_i \in \{1,...K\}$ $i \in \{1,..n\}$ samples [21, 22]. The translation vector of a bias term is denoted as, $t \in R^{K-1}$ and the weight matrix is denoted as $W \in R^{p\times(K-1)}$ A linear function of $(K-1)$ dimensional space $z_i' = x_i'W + t'$ for projected sample i. The pre-processing is required in the kernel matrix for kernel changes. Mercer's theorem satisfied definite positive nucleus are denoted as, $k : R^p \times R^p \to R^+$ and Hilbert space of corresponding reproducing core is denoted as H_k. Definition map is denoted as $\psi(x) = k(x,.)$ $k(x_i, x_j) =< \psi(x_i), \psi(x_j) > H_K$ under k action. The matrix K 's kernel matrix $n \times n$ $k(x_i, x_j)$ and the matrix $n \times l$ are defined as ψ a row $\psi(x_i)$ $K = \psi'\psi$. The simplex space maps are given in equation (14).

$$Z = \psi W + 1t' \quad (14)$$

Distance boundary of each classification measures sample i error. The distance between sample i to class k j is in equation (15).

$$q_i^{kj} = \left(x_i'W + t'\right)\left(g_k - g_j\right) \quad (15)$$

Equation (16) provides Huber hinge loss.

$$h(q) = \begin{cases} 1 - q - \left(\frac{k+1}{2}\right) & if\ q \leq -k \\ \frac{1}{2(k+1)}(1-q)^2 & if\ q \in (-k, 1] \\ 0 & if\ q > 1 \end{cases} \quad (16)$$

The l^p error is summed for each sample to provide the total error as in equation (17).

$$\left(\sum_{j=1}^{K} h^p\left(q_i^{y_i,j}\right)\right)^{\frac{1}{p}} \quad (17)$$

Optimal sample weights are denoted as $\omega i = \frac{n}{n_k K}, i \in G_k$ considering various groups of certain classification errors for extra weights. The n_k number of G_k samples and the set of samples are denoted as $G_k = \{i : y_i = k\}$ belonging to the class k. The total loss function of MSVM is given in equation (18).

$$L_{MSVM}(W,t) = \frac{i}{n}\sum_{k=1}^{K}\sum_{i\in G_k}\omega_i\left(\sum_{j\neq k}h^p(q_i^{kj})\right)^{\frac{1}{p}} + \lambda trW'W \quad (18)$$

A regularization term is denoted as, λ and overfitting is avoided by penalty term $\lambda trWW$. Ridge regression of penalty term using W vector row of a norm to reach zero. The penalty term becomes λWW if $K=2$ the loss function given in equation (18) is improved on the Huber hinge loss basis of SVM two-class, as defined in equation (19).

$$y_m = \arg\min_k \left\| z_m' - g_k' \right\|, \text{ for } k = 1,,.K \quad (19)$$

Where simplex space is mapped to optimal $z_m = x_m' W + t'$ for an unknown sample x_m, equation (19) provides a predicted class label x_m.

4. Simulation Setup

The implementation details of the Alexnet – AWOA – MSVM model are described in this section.

4.1. Datasets

BRATS 2018 [23], BRATS 2019 [23], and CE-MRI [24] datasets were used to evaluate the Alexnet – AWOA – MSVM model. The BRATS 2018 consists of 210 High-Grade Glioma (HGG) images and 75 LowGrade Glioma (LGG) images. in BRAST 2018 and 2019 datasets, there are 369 images with 214 normal images and 155 abnormal images. in CE-MRI images, there are 3064 contrast-enhanced T1-weighted MR images, including 930 slices of pituitary tumor, 1426 slices of glioma, and 708 slices of meningioma.

4.2. Metrics

Accuracy, sensitivity, and specificity metrics evaluated the Alexnet – AWOA – MSVM model. The formula for accuracy, sensitivity, and specificity was given in equations (20, 21, 22).

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (20)$$

$$Recall = \frac{TP}{TP+FN} \quad (21)$$

$$Specificity = \frac{TN}{TN+FP} \times 100 \quad (22)$$

4.3. Parameter Settings

Alexnet has 8 epochs, 0.01 learning rate, 0.1 dropout rate, and a Stochastic Gradient Descent optimizer. The 10-fold-cross validation is implemented to evaluate the performance of the Alexnet – AWOA – MSVM model.

4.4. System requirement

The system consists of 6 GB GPU, 16 GB RAM, and an Intel i7 processor was used to evaluate the Alexnet – AWOA – MSVM model. The MATLAB 2020b tool was used to test the model and evaluate the performance.

5. Results

The AlexNet – AWOA –MSVM is evaluated on BRATAS 2018/2019 and CE-MRI datasets. The quantitative and comparative analysis of the AlexNet – AWOA – MSVM model was discussed in this section.

Table 1. AlexNet - AWOA - MSVM accuracy for augmentation

Methods	Without Augmentation	With Augmentation
AlexNet	90.1	91.4
AlexNet - WOA - MSVM	91.2	93.5
AlexNet - AWOA - MSVM	95.2	96.8

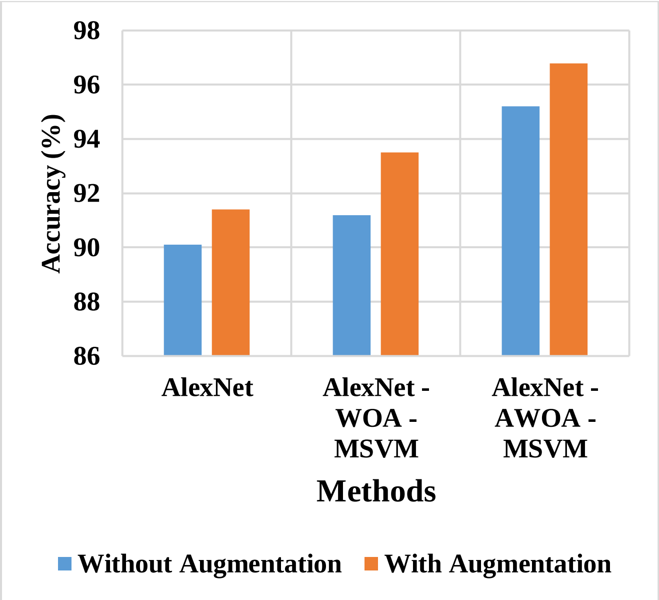

Fig. 2 Quantitative performance analysis

The quantitative performance analysis of the AlexNet – AWOA – MSVM model is explained in terms of augmentation, feature selection, and classification, as given in Figure 2 and Table 1. The augmentation method increases the classification performance due to more data for training. The AlexNet – AWOA – MSVM model shows higher classification performance than the standard AlexNet model.

The AlexNet – AWOA – MSVM have advantages in selecting the relevant features for classification for the AWOA method and MSVM model. The AlexNet – AWOA – MSVM method has 96.8 % accuracy and 95.2 % accuracy without augmentation.

Table 2. AlexNet - AWOA - MSVM model performance analysis with deep learning models

Methods	Accuracy (%)	Sensitivity (%)	Specificity (%)
ResNet18	93.7	93.6	93.7
GoogleNet	93.5	92.7	92.9
Xception	91.5	91.7	92.3
InceptionResNet V2	93.6	93.5	93.9
AlexNet	96.8	97.2	97.5

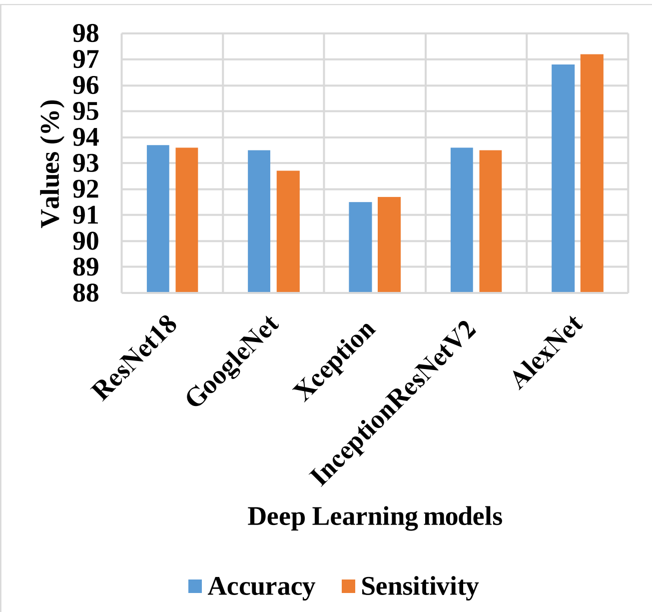

Fig. 3 Performance analysis with deep learning models

The AlexNet - AWOA – MSVM model performance is compared with other deep learning models instead of AlexNet, as given in Table 2 and Figure 3. in feature extraction, the AlexNet model performs better than ResNet18, GoogleNet, Xception, and InceptionResNetV2 models. The alexNet model has 8 layers suitable to extract relevant features for the classification. Deep learning models have the overfitting problem's limitations that affect the classification performance. ResNet18 architecture has a complex architecture that depends on Batch normalization. The AlexNet has an accuracy of 96.8 %, and the InceptionResNetV2 model has 93.6 % accuracy.

Table 3. AlexNet - AWOA - MSVM performance analysis with feature selection methods

Methods	Accuracy (%)	Sensitivity (%)	Specificity (%)
PSO	91.7	91.3	91.4
Firefly	92.6	92.5	92.7
WOA	93.5	92.4	92.6
AWOA	96.8	97.2	97.5

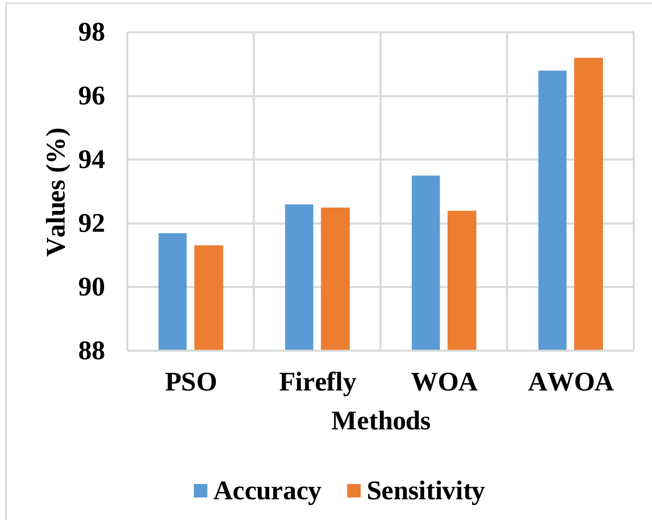

Fig. 4 Feature selection models performance analysis

The AlexNet - AWOA – MSVM model is applied with various feature selection methods for classification, as shown in Figure 4 and Table 3. The AWOA method has higher performance in feature selection due to its capacity to improve the exploitation and exploration process in the search. The WOA method has lower performance in exploration and exploitation, which degrades the performance. The Firefly method has lower convergence, and the PSO method is easily trapped into local optima. The AWOA method has higher sensitivity due to selecting relevant features in the model. The AWOA method has an accuracy of 96.8 %, and the WOA method has 93.5 % accuracy.

Table 4. Various classifier's performance analysis

Methods	Accuracy (%)	Sensitivity (%)	Specificity (%)
RF	91.2	92.3	92.6
DNN	87.4	86.5	85.3
KNN	85.3	85.2	85.1
Cubic SVM	94.2	94.1	95.2
MSVM	96.8	97.2	97.5

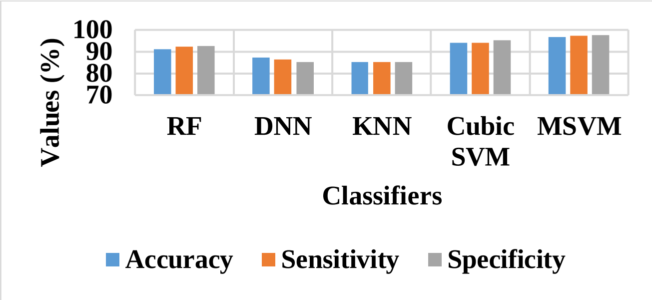

Fig. 5 Classifier models performance analysis

The AlexNet - AWOA – MSVM method is tested with various classifier models for brain tumor classification, as shown in Figure 5 and Table 4. The MSVM model has a higher capacity due to its capacity to handle high-dimensional data for classification. The KNN model is sensitive to outliers in the data, which reduces the classification performance. The cubic SVM model suffers from the limitation of imbalanced data problems in classification. The DNN and Random Forest (RF) have the limitation of overfitting problems in the classification. The MSVM classifier has 96.8 % accuracy, and Cubic SVM has 94.2 % accuracy in brain tumor classification.

5.1. Comparative Analysis

The AlexNet - AWOA – MSVM model is compared with existing research in Brain Tumour classification, as given in Table 5.

Table 5. Comparative analysis with existing methods

Methods	Dataset	Accuracy (%)
Densenet201 [11]	BRATS2018	99.7
	BRATS2019	99.8
ResNet50 [12]	CE-MRI	97.08
Two-channel DNN [13]	BRATS2018	93.69
	CE-MRI	98.04
Histogram - CNN [14]	CE-MRI	98.6
WOA - RBNN [15]	BRATS2018	96
AWOA-AlexNet	CE-MRI	99.21
	BRATS2018	99.92
	BRATS2019	99.93

The AlexNet - AWOA – MSVM is compared with existing research in Brain Tumour classification, as given in Table 5. The AlexNet - AWOA – MSVM model is tested with three datasets as BRATS2018/2019 and CE-MRI datasets. The WOA-RBNN [15] model has limitations of lower performance in exploration due to searching conditions, and the RBNN model has an overfitting problem in classification. CNN based models such as Densenet201 [11], ResNet50 [12], Two-channel DNN [13], and Histogram-CNN [14] have limitations of overfitting problem. The AWOA method increases exploration and exploitation in the search process, selecting the relevant features and reducing the overfitting problem. The MSVM model can handle high-dimensional data in the classification process. The AlexNet model has 8 layer of architecture that provides the feature extraction process. The AlexNet - AWOA – MSVM model has 99.93 % accuracy in the BRATS2019 dataset, and Densenet201 [11] method has 99.8 % accuracy.

6. Conclusion

The Reliable Brain tumor classification is important for doctors to deciding on cancer treatment. The existing deep learning models have limitations of overfitting in the classification. The AlexNet – AWOA – MSVM model is applied to solve the problem of overfitting from relevant feature selection. The AWOA method increases the search process's exploration and exploitation, increasing the relevant feature selection. The AlexNet model consists of 8 layers suitable for feature extraction, and the MSVM model effectively handles the high dimensional data. The AlexNet – AWOA – MSVM model is evaluated using three datasets such as BRATS 2018, BRATS 2019, and CE-MRI datasets. The AlexNet – AWOA – MSVM model has an accuracy of 99.93 %, and the existing Densenet201 model has 99.8 % accuracy in BRATS 2019 dataset. The future work of this model involves applying the Batch normalization and transfer learning technique to improve classification performance.

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