Deep Learning-Based Classification of Magnetic Resonance Brain Images using YOLOv5 and Lion Swarm Optimization

Zeinab F. Elsharkawy, Ahmed S. Elkorany, Said M. Elhalafawy

***Abstract*— Accurate classification of the magnetic resonance (MR) brain images is crucial for diagnosis and therapy planning. This research presents an efficient approach for MR brain image diagnoses by combining YOLOv5, the revolutionary object detection technique, with Lion Swarm Optimization (LSO). LSO, chosen for its high optimization precision, rapid convergence, and robust stability, improves YOLOv5 by efficiently fine-tuning hyperparameters and optimizing decision thresholds, resulting in higher classification accuracy (CA) and faster convergence during training. The goal is to accurately classify MR brain images into low- and high- grade gliomas (LGG & HGG) categories. YOLOv5 is employed in the suggested method to automatically identify regions of interest (ROIs) that are suggestive of HGG or LGG by detecting and localizing relevant features within MR brain images. The approach considerably increases efficiency and lowers human labor by eliminating the requirement for manual ROI selection by including YOLOv5 in the framework. To further improve the CA, the YOLOv5 model is optimized using LSO. The BRATS dataset is used to assess the suggested approach. The usefulness of the suggested approach is demonstrated by experimental findings, which outperform the other deep learning architectures and achieve an impressive Recall, Specificity, F1 score, and CA of 99%. The high accuracy highlights the potential of the proposed method as a reliable tool in clinical settings for accurate tumor classification and treatment decision-making.**

***Keywords*—Brain Image classification, Deep learning, Lion Swarm Optimization, YOLOv5**

I. INTRODUCTION

THE common tumor type in the human brain, glioma, is brought on by the unchecked proliferation of glial cells. The tumors are categorized according to histopathological standards into four grades, as stated by the World Health Organization (WHO) [1]. This grading method distinguishes the tumor grade and offers a linked prognosis for patient therapy. Two classes of tumors are defined by WHO: LGG and HGG. While HGG tumors are malignant and have grade IV stages, LGG tumors are benign and have grade II and III stages.

Precise identification of brain tumors, specifically differentiating between HGG and LGG, is essential for efficient treatment preparation and patient supervision. Because MR imaging can provide precise anatomical information, it has become a valuable modality for assessing brain tumors [2]. But interpreting MR brain images by hand is labor-intensive and subject to human mistake, thus effective and trustworthy automated techniques must be developed [3].

The accurate differentiation of HGGs and LGGs is essential for optimizing patient care, ensuring appropriate treatment planning, improving overall survival, and directly influencing prognosis and treatment strategies. HGGs are typically more aggressive, with rapid progression and poor prognosis, necessitating intensive treatment approaches such as surgery, radiation, and chemotherapy. In contrast, LGGs tend to have slower progression, and their management often involves a more conservative approach, with a focus on monitoring and delaying aggressive interventions to preserve neurological function. Misclassification of gliomas can lead to suboptimal treatment decisions—overestimating the grade may expose patients to unnecessary aggressive treatments and their associated toxicities, while underestimating the grade can result in delayed intervention, allowing tumor progression. As a result, accurate and timely separation between HGG and LGG is crucial for improving patient outcomes and creating customized treatment regimens.

In this study, we propose an efficient MR brain image diagnosis method that combines the power of YOLOv5, the revolutionary object detection technique, with LSO, a nature-inspired optimization algorithm. The primary objective is to automatically classify MR brain images into HGG and LGG categories, enabling rapid and accurate tumor diagnosis. The well-liked YOLO series has evolved, and YOLOv5 has shown remarkable performance in object detection tasks [4-8]. It

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stands out for its real-time detection capabilities and high accuracy. We intend to make use of YOLOv5's effectiveness and precision in identifying relevant features inside MR brain images for tumor classification by incorporating it into our suggested framework. LSO is used to optimize the YOLOv5 model, particularly for the task of discriminating between HGG and LGG, to further improve the classification performance. Inspired by the hunting habits of lions, LSO combines competitive and cooperative tactics to effectively explore and utilize the search space [9-12]. By exploiting this optimization approach, we intend to fine-tune the YOLOv5 model's hyper-parameters and settings, boosting its discriminatory power between HGG and LGG

The BRATS (Brain Tumor Segmentation dataset), a commonly used benchmark dataset in the field of brain tumor classification, is used to assess the suggested framework [13-15]. The BRATS dataset comprises multimodal MR images, including T1- and T2- weighted, and FLAIR sequences, in addition to the corresponding tumor segmentation masks. This dataset provides a comprehensive and diverse collection of brain tumor cases, enabling rigorous evaluation of the suggested framework.

The suggested framework is effective as demonstrated by the experimental findings, which show an astonishing 99% Recall, Specificity, F1 score and CA in categorizing MR brain images into HGG and LGG categories. Our technique has the potential to be clinically useful for precise tumor categorization and subsequent treatment decision-making, as demonstrated by its high accuracy. Our study's contribution is the combination of YOLOv5 and LSO (YOLOv5+LSO) for effective MR brain imaging diagnosis. Our goal is to give clinicians a dependable and time-efficient tool for precise tumor classification by automating the detection process using YOLOv5 and optimizing the classification model with LSO.

This paper is organized as follows. Section 2 provides a review of the relevant literature, highlighting key theories and prior research that inform the current study. Section 3 outlines the methodology, detailing the research design, data collection procedures, and analytical techniques employed. Section 4 presents the findings, supported by data analysis and visual representations. Section 5 addresses the findings' consequences, including how they coincide with or deviate from current research and their larger importance. Section 6 wraps up the work by highlighting the main findings, admitting its shortcomings, and outlining potential lines of research.

II. Literature Review

Medical image analysis is one area of computer vision that has seen a great deal of interest in the YOLO (You Only Look Once) family of object recognition methods. YOLOv5, which was released by Ultralytics, is a more recent version that improves accuracy and speed while addressing the shortcomings of its predecessors [4-8]. It has been demonstrated that YOLOv5 is beneficial for a wide range of medical applications, such as lung nodule detection [16]. YOLOv5 is a potential option for effective medical picture diagnosis due to its speed and accuracy.

Many researchers have investigated the use of MRI imaging for the detection and classification of Gliomas. The BRATS dataset's brain MRI categorization method is suggested in [17]. Three steps are involved: K-means clustering, ANN selection for the appropriate object, and texture feature extraction. Next, the classification task is performed using ANN and SVM. For ANN, the recorded CA is 94.07%. A combined system with a 98.75% CA was introduced in [18] to categorize a given MR brain picture as benign or malignant. It is based on a combination of Gray Wolf Optimizer (GWO) and SVM. To assess their performance, Artificial Neural Networks (ANN) in combination with three-optimization approaches on the BRATS challenge dataset and the Harvard database is introduced in [19]. With 97.5% accuracy, the Multi-Verse Optimizer (MFO) attained superior accuracy. KNN and SVM classifiers were used in [20] for the segmentation and classification of MR brain images, with overall accuracy of 91% and 94.6%, respectively, after using graph cut-based kernel selection. In [21], the wide residual network and pyramid pool network (WRN-PPNet) is presented for the purpose of classifying and segmenting gliomas in images from the BRATS dataset. To complete the detection process, the features are taken out of WRN and supplied into PPNet. This approach has an average DSC of 91% and sensitivity of 94%. RescueNet, a residual cyclic unpaired encoder-decoder network, is used in [22] to automatically detect brain tumors. A 94% DSC and 88% sensitivity are attained. Using a sizable dataset of MRI pictures, [23] presented a deep learning model for the categorization of gliomas into HGG and LGG. A deep learning model for the categorization of gliomas into HGG and LGG utilizing a large dataset of MRI images was presented in [23]. The method utilized 3D CNN architecture that incorporated multi-modal MRI images, achieving an accuracy of 90.5% in glioma classification. In order to distinguish between LGG and HGG, a deep feature set is taken out of the Inception-v3 model and fed into the quantum variational classifier (QVR) in [24] with CA of 90.91 %. The performance of several CNN architectures, including VGG, ResNet, and Inception, for glioma classification using MRI images is evaluated in [25]. The study found that VGG with transfer learning achieved the highest accuracy of 94.67% for glioma classification. VGG-16 is utilized in [26] for MR brain classification with 96% CA. Overall, these investigations show the promise of deep learning methods for precise and effective glioma subtype classification into HGG and LGG groups.

LSO, which is inspired by the lions' hunting behavior, is a metaheuristic optimization algorithm. It has demonstrated encouraging results while handling complicated optimization problems. Studies have applied LSO to various domains, including feature selection [27] and neural network training [28]. Cooperative and competitive techniques in LSO enable effective exploration and exploitation of the search space, making it suited for boosting the performance of machine learning models.

Individually, YOLOv5 and LSO have proven their efficacy in medical image analysis and optimization challenges, respectively. Combining these two methods should lead to

better MR brain image diagnostics, especially when it comes to differentiating between HGG and LGG. To fully investigate the potential of this combination technique and its wider applications in the field of medical imaging, more investigation and validation studies are necessary.

III. METHODOLOGY

3.1 Dataset:

The BRATS dataset [13-15], which is frequently used for MR brain image classification algorithms, is used to assess the suggested approach. A well-curated dataset comprising MR brain images of HGG and LGG cases are employed. The dataset was preprocessed to ensure uniformity and eliminate noise or artifacts that could impact classification performance. On certain dataset images, data augmentation techniques including flipping (vertical and horizontal), cropping, and rotation at various angles (from 10□ to 270□ randomly) were used to enhance the generalization performance. The obtained 1000 MR images (500 HGG and 500 LGG) were used to test the proposed model.

3.2Deep Learning Architectures

ResNet, a popular deep learning architecture, introduces skip connections to alleviate the vanishing gradient problem. We evaluated ResNet18, ResNet34, ResNet50, and ResNet101 variants for our MR brain image classification task. EfficientNet is a family of deep learning architectures known for their superior performance and efficiency. We explored EfficientNet models B0, B1, B2, and B3 for our classification experiment. A framework called YOLOv5 has demonstrated impressive performance in several computer vision applications for object detection. The YOLOv5n version is used to classify MR brain images. The input size of its images is set to 256 pixels. Treating the challenge as an object detection task allowed us to make use of YOLOv5n's speed advantage in real-time processing and its effectiveness in handling a variety of image scales.

As illustrated in Fig. 1, the YOLOv5 architecture is composed of a detecting head, a neck network, and a backbone network. Features are extracted from the input image via the backbone network. YOLOv5 provides two skeleton choices (CSPDarknet53 or CSPDarknetLite). Based on the Darknet architecture, the CSPDarknet53 backbone is made up of 53 convolutional layers and a CSP (Cross Stage Partial) module. Although it requires more calculation, it is more accurate. CSPDarknetLite is designed for situations with constrained processing resources, this is a simplified variant of the CSPDarknet53 backbone. To enhance the model's capacity to identify objects of varied sizes, the neck network is in charge of fusing features from different scales. YOLOv5 uses a PANet (Path Aggregation Network) as the neck network. PANet incorporates feature pyramid levels and combines them through a top-down and lateral connection process. The detection head completes the object detection by using the fused features from the neck network. YOLOv5 uses a series of convolutional layers to predict bounding boxes, confidence scores, and object classes. The architecture predicts bounding boxes at three different scales to handle objects of different sizes.

YOLOv5n was chosen over YOLOv4, Faster R-CNN, and other presented models for classifying LGG and HGG due to its superior balance of speed and accuracy, better performance on small datasets, and effective integration with LSO. YOLOv5 is designed to be efficient and faster, making it ideal for real-time applications. It also achieves near state-of-the-art results with simpler architecture and easier implementation compared to YOLOv4 and Faster R-CNN, which require more computational power and are more complex to set up. This makes YOLOv5 a more practical choice for medical imaging tasks where quick and accurate classification is crucial.

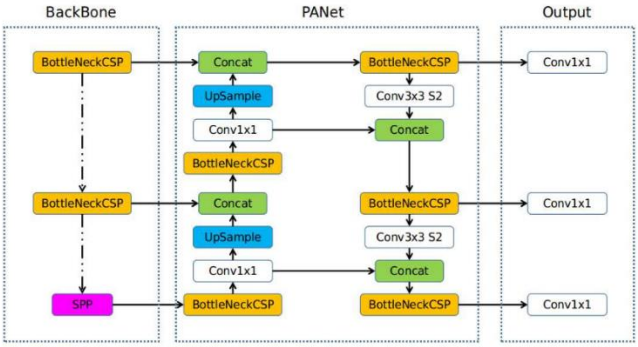

Fig. 1. The Yolov5 architecture.

3.3Lion Swarm Optimization

LSO, A swarm intelligence algorithm, mimics the actions of a lion, lioness, and cub. Its merits include high optimization precision, quick convergence, and strong stability. Neural network optimization, engineering, and continuous function optimization challenges can all be resolved with LSO. The following facets of lion society provide as inspiration for LSO. The individual holding the highest rank inside the lion group is the lion king and has priority of reproduction and food. The lion king follows the best lioness in each iteration to update its location and secure the area. Within the lion group, the lioness is the primary hunter and works in tandem with other lionesses to pursue prey. The lioness uses a crossover operation with the lion king or other lionesses and a random walk approach to update its position. The cub, who is the child of the lion king and lioness, picks up hunting skills from its parents. The cub uses either perturbation or a mutation operation to update its position. When the cub reaches adulthood, it may also be expelled from the group and reunite with other expelled cubs to create a new group.

LSO is used to improve the performance of the trained YOLOv5 model on the BRATS dataset. Integrating the LSO into YOLOv5 enhances the model's performance by optimizing hyperparameters and improving classification accuracy for LGG vs. HGG detection. Unlike conventional optimizers like SGD or Adam, LSO employs a global search mechanism that dynamically fine-tunes key

hyperparameters, such as momentum, batch size, learning rate, weight decay, and anchor box sizes. This optimization ensures that the model converges efficiently while avoiding local minima, leading to improved generalization on medical imaging datasets. The more detailed explanation is illustrated in the flowchart diagram in Fig. 2 and its steps are as follows:

- **Initialization**: a population of lion agents is initialized, each of which represents a possible solution (set of hyperparameters, such as input size, batch size, and learning rate) for the YOLOv5 model.
- **Fitness Evaluation**: For each lion, configure YOLOv5 with its hyperparameters. Train YOLOv5 on the training dataset. Each lion agent's fitness is evaluated based on the YOLOv5 performance with the corresponding hyperparameters on a validation dataset.
- **LSO Optimization Loop (Swarm Behavior)**: Lions in the swarm follow specific behaviors such as hunting, encircling prey, and attacking, which correspond to exploring the hyperparameter space, exploiting promising regions, and fine-tuning the best solutions.
- **Update and Convergence**: The hyperparameters are updated iteratively based on the lion agents' behaviors until the algorithm converges to an optimal or near-optimal set of hyperparameters.
- **Select the Best Solution:** Identify the lion with the highest fitness value, representing the optimal hyperparameters.
- **Get Optimized YOLOv5n:** configure YOLOv5n using the optimized hyperparameters. Use the training dataset to train the final model and use the testing dataset to determine the classification accuracy.

In this study, the LSO was configured with a population size of 50 lions, several iterations of 100 iterations, and 0.1 mutation rates. LSO balances exploration (searching new regions) and exploitation (refining existing solutions) by mimicking the social behavior of lions. Here's a brief overview:

- **Exploration**: Lion swarms use random walks and diverse search patterns to explore new regions of the solution space, ensuring the algorithm avoids local optima. Exploration helps identify optimal hyperparameters and network configurations, improving feature extraction for object detection
- **Exploitation**: Dominant lions refine solutions in promising regions using local search strategies, intensifying the search around high-quality solutions. Exploitation fine-tunes model parameters, enhancing precision in detecting and classifying objects

This balance enhances YOLOv5's performance by Improving feature learning, refining detection accuracy, generalization to unseen data, reducing overfitting, and improving robustness. By optimizing YOLOv5 with LSO, classification, and detection accuracy are significantly improved, making it more effective for complex tasks like medical image analysis. The suggested approach helps physicians with treatment planning and patient care by offering an automated and effective classification system for brain tumors.

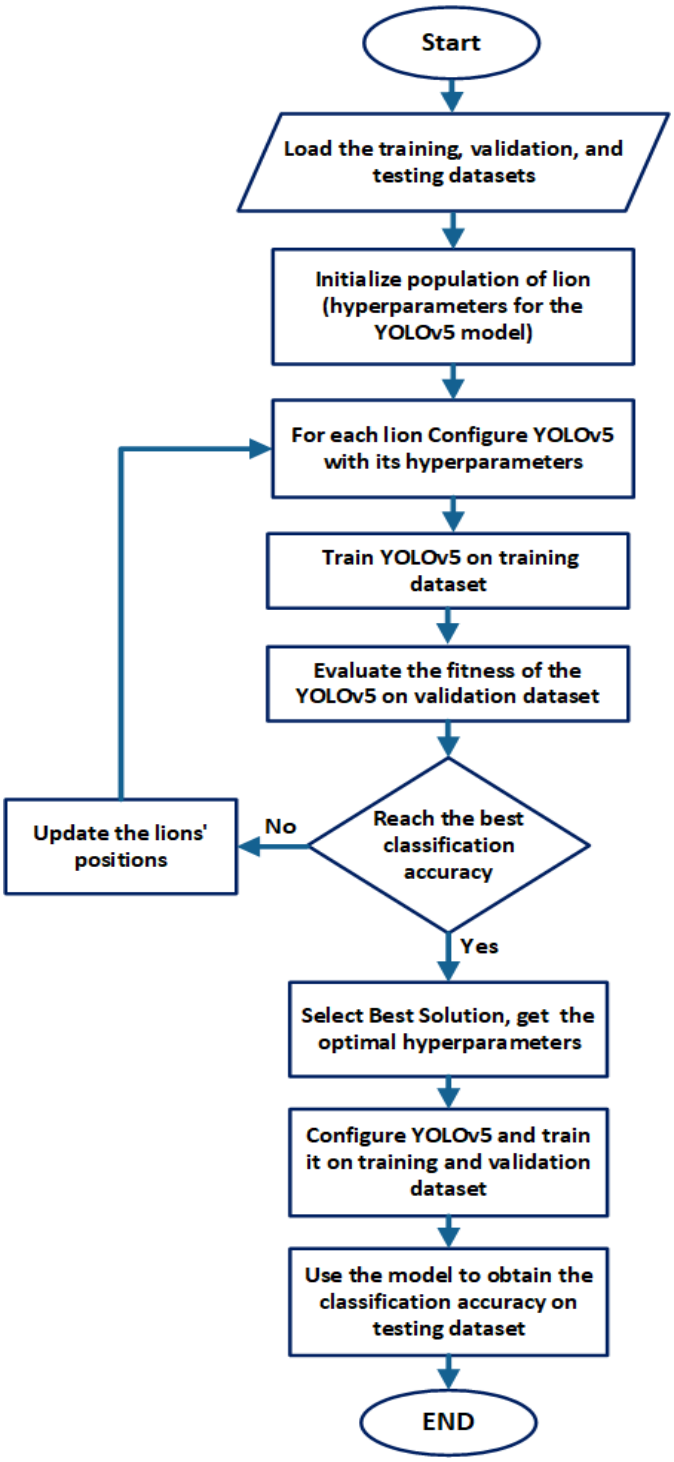

Fig. 2. The flowchart of the proposed LSO-YOLOv5n model.

IV. Experimental Results and Discussion

The same hardware and software are used for every experimental trial in this study. The machine has an Intel(R) Core (TM)i7-10870H 8-core processor, 16GB RAM, and an Nvidia GeForce RTX 3060 GPU. The following software

environment settings were used: Windows 11, CUDA Toolkit, Python, and PyTorch.

To evaluate the effectiveness of the proposed model and other DL models, we randomly divided the data set into training, validation, and testing sets, with 80%, 10%, and 10% for each model, respectively. The LSO technique is used to adjust our model's learning rate, batch size, and input size, producing 0.001, 32, and 256, respectively. Maximizing CA is the optimization function in our LSO implementation. Other metrics, like the precision, recall, specificity, confusion matrices (CMs), and F1 score, are also used to assess the performance of the model. Precision is the proportion of accurately expected positive cases (e.g., HGG) among all instances expected as positive. The high precision shows that the model has a low rate of false positives, which is crucial in medical diagnosis to prevent misdiagnosing benign cases (e.g., LGG) as malignant. Recall represents the proportion of true positive examples (e.g., HGG) properly detected by the model. Specificity refers to the fraction of actual negative cases (e.g., LGG) accurately detected by the model. The F1 score provides a balanced assessment of the model's performance. The F1 score is especially useful in imbalanced datasets. It ensures that the model works well in terms of precision and recall. The percentage of correctly identified occurrences relative to all instances is measured by CA, which offers a comprehensive performance metric. These metrices are computed as follows:

$$\text{Precision} = \frac{\text{True Positives (TP)}}{\text{TP} + \text{False Positives (FP)}}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{False Negatives (FN)}}$$

$$\text{Specificity} = \frac{\text{True Negatives (TN)}}{\text{TN} + \text{FP}}$$

$$\text{F1 Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

$$\text{CA} = \frac{TP + TN}{\text{TP} + \text{TN} + \text{FP} + \text{FN}}$$

Figures 3 and 4 display training MR brain image samples and the YOLOv5+LSO classification outcomes, respectively. The CA and training loss of several optimizers employing YOLOv5 and our suggested YOLOv5n+LSO model across 300 epochs are shown in Figures 5 and 6, respectively. These results highlight the superior training capability of the YOLOv5n+LSO model compared to other optimizers. Notably, the RMSProp optimizer yielded the worst performance in terms of both accuracy and loss.

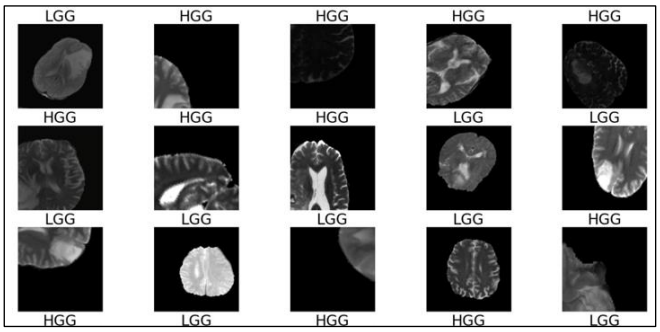

Fig. 3. Sample training MR brain images.

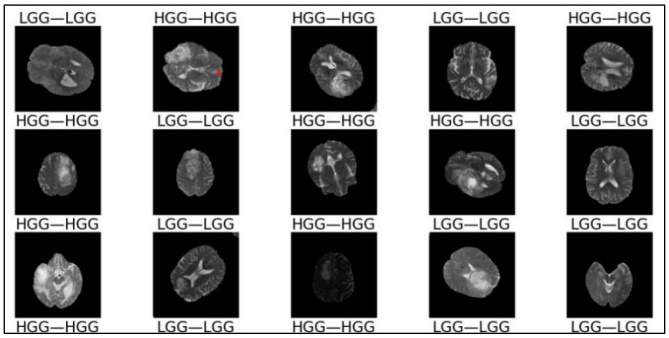

Fig. 4. Samples of classification results of Yolov5 and LSO.

Figure 5 shows that up to 160 epochs, the training accuracy of Adam, AdamW, SGD, and LSO optimizers converges. Nevertheless, the Lion optimizer works better than the others and keeps improving until training is finished, reaching higher accuracy after 160 epochs. This suggests that the LSO optimizer excels in refining the model's learning process during later stages of training. Similarly, Figure 6 reveals that the training loss for Adam, AdamW, and LSO optimizers converges closely during the initial and middle phases of training. However, in the final stages (i.e., from 250 to 300 epochs), the LSO optimizer achieves the lowest training loss, further underscoring its effectiveness in minimizing errors and enhancing model performance.

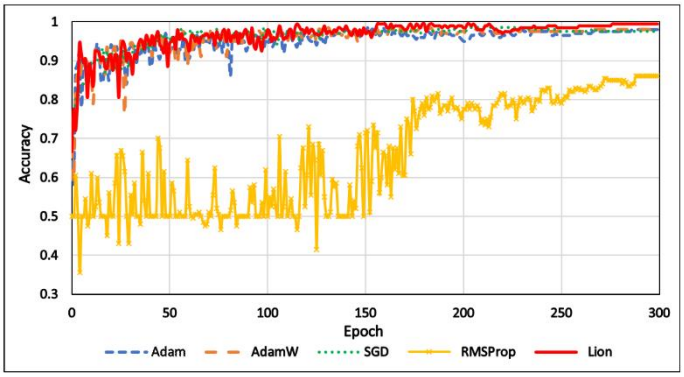

Fig. 5. CA comparison of different optimizers with Yolov5.

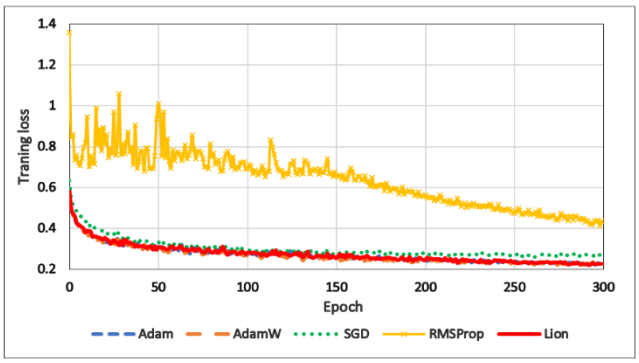

Fig. 6. Training loss comparison of different optimizers with Yolov5.

These findings demonstrate that the Lion optimizer not only achieves higher classification accuracy but also exhibits better optimization of the loss function, particularly in the later epochs. This makes it a robust choice for training YOLOv5n in complex tasks such as medical image classification, where precision and stability are critical. Table 1 shows the CMs and CAs of the suggested model along with other similar DL models. Table 2 compares the proposed method's performance with several other DL techniques. Our model can classify the MR brain images with the highest accuracy of 99% based on the obtained results that are shown in these Figures and Tables. Whereas one image from each of HGG and LGG is misclassified. The proposed model outperforms other DL models in CA, Recall, and F1-Score. In contrast to our model, Efficient_B3 achieves lower recall, F1-Score, CA, and greater precision and specificity.

TABLE 1
CAS AND CONFUSION MATRICES OF PROPOSED AND DIFFERENT DL METHODS

Method	All	HGG	LGG
Efficient_b0	98	97	99
Efficient_b1	97.5	98	97
Efficient_b2	97.5	96	99
Efficient_b3	98	96	100
Resnet18	93	93	93
Resnet34	93	96	90
Resnet50	93	90	96
Resnet101	95.5	95	96
Yolov5S	97.5	99	96
Yolov5n_sgd	98	98	98
Yolov5n_adam	98	99	97
Yolov5n_adamw	98	97	99
Yolov5n_RMSProp	86	75	79
Yolov5n_LSO	**99**	**99**	**99**

This is because the HGG is classified with 96% by the Efficient_B3 whereas the LGG is 100%. Furthermore, Table 3 provides a comparison of our model with other published models that utilized the BRAST dataset. CA, Recall, Specificity, and F1 Score are used to evaluate these models. As shown in Table 3 the suggested model outperforms other already published models with an impressive Recall, Specificity, F1 score, and CA of 99%.

TABLE 2
THE PERFORMANCES OF SEVERAL OTHER DL TECHNIQUES

Method	Specificity %	Precision %	Recall%	F1Score (DSC)%	CA%
Efficient_b0	99	98.98	97	97.98	98
Efficient_b1	97	97.03	98	97.51	97.5
Efficient_b2	99	98.97	96	97.46	97.5
Efficient_b3	100	100	96	97.96	98
Resnet18	93	93	93	93	93
Resnet34	90	90.57	96	93.2	93
Resnet50	96	95.74	90	92.78	93
Resnet101	96	9596	95	95.48	95.5
Yolov5n_SGD	94	94.12	96	95.05	95
Yolov5n_Adam	96	96.12	99	97.54	97.5
Yolov5n_LSO	**99**	**99**	**99**	**99**	**99**

TABLE 3
COMPARISON OF CA VALUES ON THE BRATS DATASET

Paper	Method	Recall%	Specificity %	F1 score%	CA%
[29] 2021	SVM classifier	87	75.9	-	84.1
[17] 2019	K-Mean- ANN	90.09	96.87	-	94.07
	K-Mean- SVM	87.45	91.32	-	90.72
[18] 2019	GWO-SVMs	95	100	97.44	98.75
[19] 2020	ANN +MVO	98.33	100	99.16	98.7
	ANN + SSA	95	100	97.44	96.25
	ANN +MFO	96.67	100	98.31	97.5
[20] 2023	GBKS GC+SVM	96	97	-	94.6
	GBKS GC+kNN	82	93	-	91
[24] 2022	Incptionv3+QVR	91	-	91	90.91
[26] 2023	VGG 16	100	93.33	96.30	96
[30] 2022	DCNN+SVM	-	-	-	95.83
Ours	**YOLOv5n_LSO**	**99**	**99**	**99**	**99**

This study identified one misclassified image from each category (HGG and LGG), revealing key challenges in glioma classification. Misclassifications tend to happen when tumors present with ambiguous features, such as low-contrast boundaries in HGGs or abnormal enhancement in LGGs. Noise artifacts, and the natural spectrum of glioma heterogeneity are further complicated the classification process. Addressing these issues might involve improved preprocessing (i.e., denoising or bias field correction) or leveraging more sophisticated architectures, like attention-based CNNs or YOLO, to capture subtle distinguishing features.

V. Conclusion

This research proposes an effective framework for MR brain image diagnostics that combines the strengths of YOLOv5 and LSO. Through automation of ROI selection and optimization of the classification model, the suggested approach attains remarkable precision in differentiating between HGG and LGG. The proposed method is evaluated on the BRATS dataset. Based on the testing results, the suggested method surpassed the state-of-the-art methods by a significant margin, achieving remarkable Recall, Specificity, F1 score, and CA of 99%. Its improved generalization capabilities, more efficient optimization, and superior feature extraction are the reasons behind this. For the specific task of classifying LGG and HGG tumors, LSO's ability to balance exploration and exploitation results in fine-tuned YOLOv5n that achieves higher F1 score, specificity, recall, and CA. Hence the proposed method provides a reliable classification of MR images, which may lead to improvements in brain tumor diagnosis and therapy. To confirm the YOLOv5+LSO framework's robustness and generalizability, future research initiatives will involve looking at additional datasets. Using multimodal fusion to improve diagnosis accuracy also involves adding other modalities, such as CT and PET.

Data Availability

The datasets analyzed during the current study are publicly available in the (Multimodal Brain Tumor Segmentation Challenge2015, Multimodal Brain Tumor Segmentation Challenge 2018 and 2020 repositories, (https://www.smir.ch/BRATS/Start2015, https://www.med.upenn.edu/cbica/brats2018/data.html, and https://www.med.upenn.edu/cbica/brats2020/data.html).

Competing Interests

The authors declare that there is no conflict of interest.

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