DOI: 10.1109/ICAC57885.2023.10275235

# Automated Models for the Classification of Magnetic Resonance Brain Tumour Images

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***Abstract*—Brain tumours are the second largest cause of cancer death in children under 15 and young adults until age 34. Also, among people over 65, these tumours are the second-fastest-growing cause of cancer death. Computer-assisted tumour diagnosis is challenging, and efforts to increase the accuracy of tumour classification and generalisation are continually being made despite the plethora of studies conducted. This study of automated multi-class brain tumour classification utilising Magnetic Resonance Images aims to design and develop three automatic brain tumour classification approaches to categorise the brain tumours as glioma, meningioma, and pituitary tumours, which assist clinicians in making brain tumour diagnoses and developing further treatment plans to save patient's life. This research proposes a transfer learning approach using ResNet 50, hand-crafted features with machine learning classifiers, and a hybrid firefly-optimised multi-class classifier for tumour classification. The hybrid methodology yields the highest classification accuracy of 99% using the Figshare dataset. Furthermore, using the Figshare dataset, the hybrid technique yields the highest sensitivity (recall) of 99% for meningioma and pituitary tumours, the highest precision of 100% for pituitary tumours, and the highest F1-measure of 99% for pituitary tumours.**

***Keywords*—Brain Tumour Classification, Meningioma, Glioma, Pituitary, Deep Learning, Machine Learning, Resnet 50, MRI.**

## I. INTRODUCTION

Brain tumours are a significant concern in the United Kingdom, affecting thousands of individuals each year. According to Cancer Research UK, around 11,400 new cases are diagnosed annually, spanning various age groups and causing symptoms such as headaches, seizures, and mood changes. "A brain tumour occurs as a result of an abnormal growth or spread of cells from within the brain or its supporting tissues that can damage the brain or threaten its function" [1]. A brain tumour is characterised as the abnormal development of cancerous cells in the brain, which may be benign or malignant [2]. MRI is one of the most important and commonly used techniques for detecting and diagnosing brain tumours, as it can produce highly detailed images of soft tissues, such as brain cells and their connections. Deep learning-based classification algorithms have recently outperformed conventional machine learning techniques for brain tumour diagnosis in terms of time and accuracy [3].

Segmentation and classification are two critical challenges in analysing brain tumour images. Although there are many methods for segmenting images, it is still necessary to introduce practical, quick methods for segmenting medical images [4]. In the medical area, the classification of MR brain images is becoming increasingly significant since it is essential for planning treatment, diagnosing problems, measuring tissue volume to examine tumour growth, and analysing the anatomical structure and patient's subsequent procedure. Medical image analysis methods are frequently utilised to find anomalies in human anatomy in scan images [5]. MRI scans use medical image processing techniques to identify various types of tumours. The process starts with image pre-processing to correct intensity non-uniformities, remove noise, and enhance the contrast between tumour and non-tumour regions. After pre-processing, relevant features or characteristics are extracted from the images for classification. These features can include texture, shape, and intensity of regions within the image. The most relevant features are then selected to reduce the problem's dimensionality and improve classification performance. The next step involves using machine learning algorithms such as support vector machines (SVMs), random forests, and artificial neural networks for tumour classification. Finally, post-processing techniques are used to refine and analyse the results to improve accuracy.

In the conventional method of manual diagnosis, radiologists use brain scans to locate and characterise lesions, and they may also extract tissue for a pathological diagnosis. Pathologists then take the tissue, analyse it under a microscope, and assess the grade. While conventional diagnosis can detect and categorise different tumour stages depending on prognosis, computer-assisted technology enhances diagnosis accuracy. Furthermore, human detection of the visible features of the image is limited, which increases the risk of human error in conventional classification methods. Therefore, automated classification will always be helpful, especially for large MRI brain tumour datasets.

This study proposes three automated brain tumour classification approaches, using image processing techniques and machine learning techniques, to categorise the brain tumours as glioma, meningioma, and pituitary tumours, which assist clinicians in making brain tumour diagnoses and developing further treatment plans to save patient's life. The challenges in this research work include the lack of integration of different deep learning techniques, the need for labeled datasets, difficulty in integrating multiple datasets due to variations in hardware and protocols, the requirement for brain image segmentation, and the selection and extraction of relevant features. These challenges are addressed through data augmentation, the use of figshare dataset with Region of Interest (ROI), and the implementation of a hybrid model to enhance the analysis and classification of MR brain tumor images

The remaining section of this paper is arranged in the following manner. Section 2 described the review of brain tumour classification strategies implemented with the Figshare dataset, whereas Section 3 discussed the background of automated multi-class tumour classification. Also, the proposed models, along with detailed architectures and descriptions, are shown in section 4. Section 5 discussed the experimental results and compare our proposed model with existing methods using the Figshare dataset. Finally, Section 6

summarises this paper with some concluding remarks and future enhancements.

## II. LITERATURE SURVEY

A fundamental step that reduces the probability of suffering a fatal outcome is identifying and analysing the brain tumour in its initial stages. To determine the proximity of brain tumours using AI techniques, many analysts directed multiple examinations and selected a few models. These DL techniques differ from conventional ones because they do not rely on labour-intensive feature extraction techniques. The hierarchy of features is automatically learnt in DL approaches, including learning complex features straight from sample data. The Convolutional Encoder Network (CEN), CNN, U-Net CNN, Long Short-Term Memory (LSTM), and dual-force CNN are provided to detect the brain tumour [8].

To categorise brain tumour types into gliomas, meningiomas, and pituitary tumours, Cheng et al. [9] created an open brain tumour dataset. This study utilised three approaches to analyse the Figshare dataset: bag-of-words, grey-level co-occurrence matrix, and intensity histogram. With a classification accuracy of 91.28%, the bag-of-words methodology on the SVM classifier outperformed the other two approaches. However, this categorisation approach requires manual labelling, awareness of the existence of the tumour, and zooming onto the tumour or region of interest.

To categorise MR tumour images in the Figshare dataset into gliomas, meningiomas, and pituitary tumours, Paul et al. [10] utilised three classification models, including Vanilla CNN, a fully connected neural network and random forest. With Vanilla CNN and an image size of 256 by 256, the ideal classification accuracy was 91.43%. Paul et al. intend to include coronal and sagittal pictures as part of a follow-up study to expand the dataset and offer insights into tumour types that are challenging to view from just one angle.

The capsule networks utilised by Afshar et al. [11] also categorised tumours based on the figshare dataset. They asserted that the segmented tumours outperformed the whole brain images in terms of the performance of the capsule net. The Figshare dataset's raw brain images had a classification accuracy of 72.13%, while segmented tumours had an accuracy of 86.56%. After ten epochs, the learning phase was terminated.

Afshar et al. [12] used MR images along with the coarse tumour boundaries as additional inputs in their subsequent paper to fine-tune the focus of the CapsNet. They concluded by concatenating the output of the capsule layer with the vector representing the tumour border and processing it through a sequence of fully connected layers. Thus, gliomas, meningiomas, and pituitary tumours were classified as different brain tumours by Afshar et al. with an enhanced classification accuracy of 90.89%.

Phaye et al. [13] investigated various capsule network designs on this dataset. They concluded that diversified CapsNet would produce the best accuracy, with a claimed accuracy of 95.03%.
In this figshare data set, seven different neural networks were examined by Abiwinanda et al. [14]. The best performance was achieved with CNN, which had a validation and training accuracy of 84.19% and 98.51%, respectively. In upcoming work, they added a colour-balancing step to CNN to increase classification accuracy and reduce overfitting.

By using the same dataset to create a genetic algorithm for multi-class brain tumour classification, Anaraki et al. [15] increased CNN accuracy. The classification accuracy they received was 94.2% at best. The proposed CNN architecture increased result accuracy without requiring time-consuming procedures like segmentation or skull stripping. The decision was just made using the raw MR image data. To achieve an accuracy of 94.82% under five-fold cross-validation,

Swati et al. [16] employed a pre-trained deep CNN model. They also suggested a transfer learning-based block-wise fine-tuning approach.

Zhou et al. [17] used comprehensive 3D MR images to screen for and classify brain tumours using an LSTM-based network. They used an autoencoder to extract features from the axial view and an LSTM to categorise the scans. They added zero matrices to each image to test their results on this dataset since the primary dataset only contains selected slices. They reported a multi-class tumour classification accuracy of 92.13%.

Refaat et al. [18] utilised machine learning classifiers such as Support Vector Machines, K-Nearest Neighbor, and Generalized Regression Neural Networks to increase the classification accuracy by relying on the figshare dataset. The features are extracted using GLCM followed by pre-processing such as normalisation and PCA, bayesian optimisation and classification. The classification accuracies of the algorithms used in diagnosing tumours are 97%, 96.24%, and 94.7% for K-Nearest Neighbor, Support Vector Machines, and Generalized Regression Neural Networks, respectively.

The use of a pre-trained deep neural network as a discriminator in a Generative Adversarial Network (GAN) was suggested by Ghassemi et al. [19] to extract robust features and understand the structure of MR images in their convolutional layers.

The literature has reported several research studies on multi-class tumour classification. Due to the irregularity of tumour shape, these methods couldn't yield a good classification accuracy for these tumour types. This paper proposes three automated classification models in this dissertation to distinguish between gliomas, meningiomas, and pituitary tumour types. Due to the irregular tumour shape, these methods offered a better classification accuracy for these tumour types.

## III. BACKGROUND

Medical imaging techniques and processes are utilised in digital health to obtain images of various brain areas for diagnostic and therapeutic purposes. Despite numerous significant efforts and promising results in this space, reliable segmentation and classification utilising modalities such as MRI still need improvement.

### *A. Clinical Background*

Clinical experts classify brain tumours as primary or secondary tumours based on their start and spread. Primary brain tumours emerge from brain cells or the adjacent regions of the brain. It has defined boundaries and tends to adhere to them. It is further classified as glial or non-glial, benign or malignant tumours. Glial tumours, often known as gliomas, emerge from the glia cells, which are further classified as astrocytes, ependymal cells, oligodendroglial cells or oligos, Schwann cells, microglia, and satellite cells [6]. Non-glial tumours originate on or in the brain's cellular components, such as the neurons, blood vessels, and glands.

Gliomas, meningiomas, and pituitary tumours are a few primary brain tumours. Glioma is a tumour that develops in brain structures other than nerve cells and blood vessels. Meningiomas, on the other hand, originate from the membranes that encase the central nervous system and cover the brain, whereas pituitary tumours are nodules that rest inside the skull. It is crucial for clinical diagnosis and subsequent

practical patient evaluation that these three types of tumours are precisely distinguished.

### *B. Dataset*

The publicly accessible dataset used in this study to test and calibrate Cheng et al.'s [7] approach for classifying multi-class brain tumours in MR images was first proposed in 2017. There are 3064 T1-weighted, contrast-enhanced MR images in this Figshare dataset from 233 patients with three distinct types of brain tumours: meningioma (708 images), glioma (1426 images), and pituitary tumour (930 images). The axial, sagittal, and coronal planes of all three MR images are included in this collection.

### *C. Performance metrics*

The performance metrics mainly determine the effectiveness of the method. Sensitivity (Recall), precision, accuracy, and F1 score are considered as measures to evaluate the study's results using the equations (1) – (4). The confusion matrix, as shown in Figure 1, is used to present the prediction of these metrics' values.

| TRUE CLASS \ PREDICTED CLASS | |
|---|---|
| **TRUE POSITIVE (TP)** | **FALSE NEGATIVE (FN)** |
| **FALSE POSITIVE (FP)** | **TRUE NEGATIVE (TN)** |

**Figure 1: Confusion Matrix**

$$\text{Precision} = \frac{TP}{TP+FP} \quad (1)$$

$$\text{Sensitivity} = \frac{TP}{TP+FN} \quad (2)$$

$$\text{F1 Score} = \frac{2*(\text{Precision} * \text{Sensitivity (Recall)})}{(\text{Precision}+\text{Sensitivity (Recall)})} \quad (3)$$

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (4)$$

## IV. PROPOSED METHODOLOGY

This research aims to design and develop an automated brain tumour classification approach to categorise the brain tumours as meningioma, glioma and pituitary. The proposed methodology involves three models, each of which effectively utilises various phases of medical image processing, such as pre-processing, data augmentation, features extraction, features optimisation and classification.

### *1. Transfer learning approach using ResNet 50*

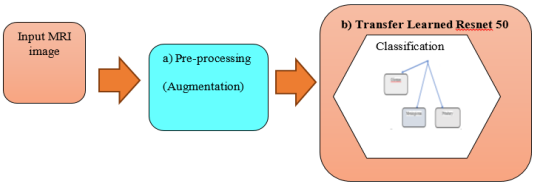


**Figure 2: ResNet 50 for multi-class classification**

The input MRI brain image is fed to the pre-processing phase in this transfer-learned model. Data augmentation methods such as flipping and rotation raise the MRI slice count to 24512 for enhanced accuracy. Then, the tumour classification is performed to classify the tumours into gliomas, meningiomas, and pituitary tumours using the transfer learned ResNet 50 model, which can effectively handle complex visual patterns and features in brain tumor classification tasks. Its depth, skip connections, and pre-training capabilities make it a suitable choice for capturing intricate details in MRI images and achieving high classification accuracy.

Figure 2 shows the proposed architecture of transfer learned ResNet 50 to categorise tumours in MRI into gliomas, meningiomas, and pituitary tumours. In our studies, we eliminated the final fully connected deep shortcut module. We included three new sets of linear modules, two new sets of Leaky Relu, two new sets of dropout modules, and a softmax classification module designed for our dataset classification. As a result, the number of transfer learning layers in ResNet 50 grew from 174 to 181. Figure 3 depicts the structure of the proposed ResNet 50 on the transfer learning model.

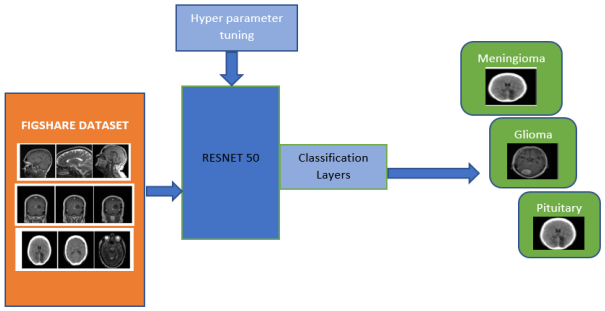


**Figure 3: ResNet 50 on transfer learning Architecture**

By eliminating the final layer (Linear-174) of ResNet 50, new layers such as linear, Leaky ReLu, dropout, and softmax are introduced successively to classify figshare MR image data into glioma, meningioma, and pituitary tumour types. The train and test datasets were split in the ratio of 70-30. Heuristically changing the network's hyperparameters made it easier for the loss function to converge during training. The hyperparameter settings of our experiment are listed in Table 1. A confusion matrix presents a tabular summary of accurate and inaccurate classifications. The confusion matrix of the suggested classifier is depicted in Table 2.

| Model | Parameters | Settings (values) |
|---|---|---|
| Transfer learned ResNet 50 deep network. | Initial Learning rate | 0.003 |
| | Momentum | 0.9 |
| | Batch size | 2144 |
| | Optimizer | Stochastic |
| | Loss function | CrossEntropyLoss |
| | Epochs | 10 |

**Table 1: Experimental parameters**

| Actual | | Predicted | | |
|---|---|---|---|---|
| | | Meningioma | Glioma | Pituitary |
| | Meningioma | 892 | 24 | 87 |
| | Glioma | 15 | 1680 | 1 |
| | Pituitary | 5 | 0 | 976 |

**Table 2: Confusion matrix of Transfer Learning Classifier**

According to the classifier's performance for each tumour category, various metrics can be produced from the confusion matrix. The proposed system's performance for each class is displayed in Table 3. The F1-score, a crucial statistical classification measure, is produced for each class by the harmonic mean of precision and sensitivity (recall). The

overall design's performance is implemented with 5-fold cross-validation, which achieves the maximum accuracy at 96% using the hyperparameters listed in Table 1.

| | Precision | Sensitivity (Recall) | F1 Score |
|---|---|---|---|
| Meningioma | 98% | 89% | 93% |
| Glioma | 99% | 99% | 99% |
| Pituitary | 92% | 99% | 95% |
| Accuracy | | 96% | |

**Table 3: Classification report: Transfer learning using ResNet 50**

**2. *Hand-crafted (Manual) feature extraction and ML classifiers***

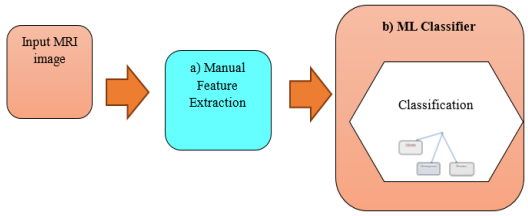


**Figure 4: Manual feature Extraction and ML classifiers for multi-class classification**

Figure 4 shows the proposed Manual feature extraction and Machine Learning (ML) classifier model for multi-class tumour classification. The recognised tumour regions are analysed to obtain five statistical features: mean, standard deviation, entropy, kurtosis and skewness. The mean provides information about overall intensity, while standard deviation reflects heterogeneity within the tumor. Entropy quantifies randomness and complexity, kurtosis indicates shape abnormalities, and skewness measures asymmetry. These features enable differentiation between tumor types by capturing variations in intensity, texture, and distribution. Finally, SVM, Random forest, Naive Bayes and Decision tree are used to categorise the brain tumours in this proposed hand-crafted feature extraction followed by ML classifier methodology. The train and test datasets were split in the ratio of 70-30. Table 4 to 7 shows the classification report based on SVM, Random forest, Naive Bayes and Decision tree classifiers with an accuracy of 79%, 79%, 59%, and 74%, respectively.

*ML Classifier*

SVM is one of the most supervised AI-enabled classification algorithms because it has higher accuracy and computational efficiency. The hyperparameter settings are RBF as kernel, decision function as One-vs-One (OVO), regularisation parameter C as [1, 10, 100, 1000, 10000] and gamma parameter (regulates the distance of the impact of a single training point) as [0.0001, 0.001, 0.01, 0.1, 1]. The OVO strategy is often utilised for converting multi-class classification issues into multiple binary classification problems.

Random forest is a versatile and straightforward supervised machine learning algorithm that produces excellent results even when no parameters are given. The forest that is the collective of the decision tresses is trained using the bagging approach. The learning models are coupled to provide a high-quality end product compared to others. This approach uses multiple decision trees before combining them into a single one. The hyperparameter settings are max_depth as [10, 20, 30, 40], min_samples_leaf as [2, 4, 5], min_samples_split as [2, 5, 10] and n_estimators as [200, 400, 600, 800, 1000, 1200, 1400].

Naive Bayes classification is a supervised classification method based on the Bayes theorem of probability and a probabilistic approach with strong (naive) independence assumptions.

A decision Tree, a supervised learning algorithm based on the divide and conquer approach, performs classification like a decision analysis and is comparable to a conditional control statement. When trees grow deep enough, the issue of over-fitting arises. It resembles a tree structure where each node stands for a feature that determines the outcome. Each leaf node holds details about the class label. Features serve as the internal nodes, and classes serve as the tree's leaf nodes.

| | Precision | Sensitivity (Recall) | F1 score |
|---|---|---|---|
| Meningioma | 63% | 62% | 62% |
| Glioma | 82% | 81% | 81% |
| Pituitary | 86% | 90% | 88% |
| Accuracy | | 79% | |

**Table 4: Classification Report: SVM**

| | Precision | Sensitivity (Recall) | F1 Score |
|---|---|---|---|
| Meningioma | 63% | 58% | 60% |
| Glioma | 82% | 80% | 81% |
| Pituitary | 85% | 92% | 89% |
| Accuracy | | 79% | |

**Table 5: Classification Report: Random Forest**

| | Precision | Sensitivity (Recall) | F1 Score |
|---|---|---|---|
| Meningioma | 49% | 10% | 17% |
| Glioma | 56% | 80% | 66% |
| Pituitary | 68% | 66% | 67% |
| Accuracy | | 59% | |

**Table 6: Classification Report: Naive Bayes**

| | Precision | Sensitivity (Recall) | F1 Score |
|---|---|---|---|
| Meningioma | 59% | 56% | 56% |
| Glioma | 77% | 76% | 77% |
| Pituitary | 81% | 84% | 83% |
| Accuracy | | 74% | |

**Table 7: Classification Report: Decision Tree**

***3. Hybrid Firefly Optimized Multi-class classifier***

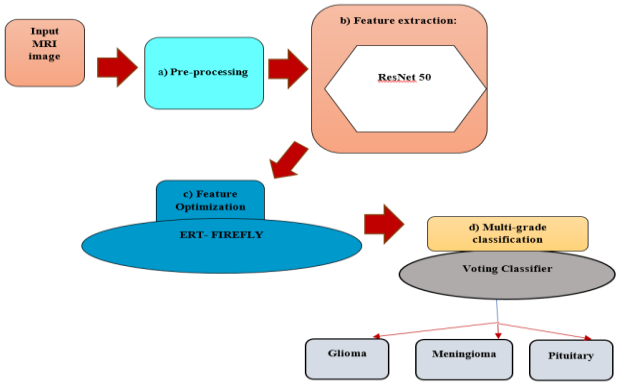


**Figure 5: A hybrid framework for multi-class classification**

The hybrid framework, as shown in Figure 5 for multi-class brain tumour classification, constitutes a pre-processing module, a transfer

learned ResNet 50 model for feature extraction, a gain-based classifier followed by a nature-inspired Firefly algorithm for feature optimisation and a voting classifier for the classification of MR images into glioma, meningioma, and pituitary tumour classes.

*Gain based classifier:* Extremely Randomised Trees Classifier (ERT), a gain-based classifier, is an instance of ensemble learning that generates a classification outcome by integrating the outputs of various de-correlated decision trees gathered in a "forest" to construct a single classification result. ERT is an extension of Random Forest in which a second randomisation stage is added to select the cut-points and the randomised assignment of attributes. The structures of randomised trees are independent of training sample outputs. The parameters of the ERT should be tuned for each specific case. ResNet 50 extracted a total of 32768 features from the brain tumour MRIs. In our method, there are 10 extra trees in the ensemble, and the predicted features count is 3592.

*Firefly algorithm:* Yang et al. [21] developed the firefly algorithm, a metaheuristic algorithm inspired by the behaviour of fireflies and the bioluminescent communication phenomenon. Yang built the Firefly algorithm based on the following presumptions:

- Due to their unisexual nature, fireflies will be lured to each other regardless of sex.
- Attractiveness is inversely correlated with brightness, so the less attractive firefly will be drawn to the more attractive firefly. But as the distance increased between the two fireflies, the attractiveness shrank.
- Fireflies will flit about randomly if their brightness is constant.

The light intensity varies with the equation,

$$I = I_0\, e^{-\gamma r^2} \quad (5)$$

where $I_0$ is the light intensity at r = 0.

The fluctuation in attraction varies with the distance r.

$$\beta = \beta_0\, e^{-\gamma r^2} \quad (6)$$

where $\beta_0$ is the attractiveness at r = 0, $\gamma$ is the media light absorption coefficient, and r is the Cartesian distance between any two fireflies *i* and *j* at $x_i$ and $x_j$ in d dimension future space, respectively.

$$r = \sqrt{\sum_{k=1}^{d} (xik - xjk)^2} \quad (7)$$

A firefly i moves toward another firefly j when it notices it is more alluring (brighter).

$$x_i^{t+1} = x_i^t + \beta_0\, e^{-\gamma r^2_{ij}} (x_j^t - x_i^t) + \alpha_t \epsilon_i^t \quad (8)$$

The second term is due to the attraction, while the third term is the randomisation parameter. When $\beta_0 = 0$, it becomes a simple random walk, whereas $\gamma = 0$ reduces to a particle swarm optimisation variant.

*Voting classifier:* A voting classifier is a machine learning estimator that trains various estimators and makes predictions by aggregating their results. The aggregating criteria are obtained by the combined voting decision for each estimator's prediction. In this module, the voting classifier predicts the accuracy from the average of Gaussian Naive Bayes, K-Nearest Neighbour and C-Support Vector Classifier (SVC) predictions. SVC performs multi-classification using a one-to-one mechanism. The train and test datasets were split in the ratio of 70-30. Table 8 shows the workflow of the hybrid firefly optimised classifier. Table 9 shows the classification report based on a hybrid framework with an accuracy of 99%, sensitivity (recall) of 99%, precision of 99%, and F1-measure of 99% using the Figshare dataset. Table 10 compares classification accuracy and methodologies of recent literature on multi-class classification using the Figshare dataset. The proposed hybrid model yields an accuracy of 99% for multi-class brain tumour classification compared to the current methodologies mentioned in the literature review.

| |
|---|
| Input: Matrix X (m,n), where X is the dataset after feature selection by ERT; m is the number of samples, n is the number of selected features |
| Output: Optimal Features |
| Procedure |
| Read the dataset containing features output by ERT and convert it into a swarm containing fireflies. |
| Apply firefly algorithm with α (randomization parameter) =1, β (attraction parameter) = 0.5 , γ (light intensity coefficiency) = 1 |
| Evaluate the fitness value of each firefly and update position based on intensity until an optimal solution |
| Optimal features are given to the voting classifier for the best classification accuracy. |

**Table 8: Hybrid Firefly optimised multi-class classifier.**

| | Precision | Sensitivity (Recall) | F1 Score |
|---|---|---|---|
| Meningioma | 97% | 99% | 98% |
| Glioma | 99% | 97% | 98% |
| Pituitary | 100% | 99% | 99% |
| Accuracy | 99% | | |

**Table 9: Classification Report: Hybrid Framework**

## V. EXPERIMENTAL ANALYSIS AND DISCUSSIONS

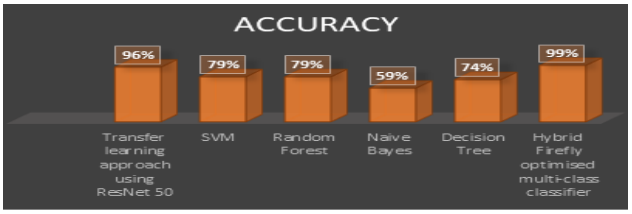


**Figure 6: Quantitative comparison results of proposed classifiers**

Figure 6 illustrates the quantitative comparison results of the proposed classifiers. The proposed research involves three domain models: transfer learning on ResNet 50, manual feature extraction and ML classifiers (SVM, RF, NB, DT) and hybrid firefly-optimised multi-class classifier. The train and test datasets were split in the ratio of 70-30 in all three proposed models. The proposed transfer learning architecture used transfer learned ResNet 50 network to extract features from brain tumours Magnetic Resonance Images. These features, along with hyperparameters such as initial learning rate, momentum, batch size, optimiser, loss function, epochs and dropout, were properly tuned to categorise MR brain images with several tumour types, including glioma, meningioma, and pituitary tumours. Among all the cutting-edge methodologies, the system's classification accuracy was 96%. However, the hyperparameter tuning and training time is a hassle during the implementation of this model. This can be overcome with the second model, where hand-crafted features such as mean, standard deviation, entropy, kurtosis, and skewness are used, whilst the accuracy is less than the transfer learning model. The highest accuracy is achieved by SVM and RF, both of which have an accuracy of 79%, followed by DT with an accuracy of 74%, and NB with an accuracy of 59%. In the third method, which uses a hybrid architecture, features are extracted using ResNet 50 and optimised using ERT, followed by the firefly swarm intelligence algorithm. The optimised hybrid method has the highest

accuracy of 99% using the Figshare dataset with an improved training time.

| State-of-the-art methods / Year | Methodology | Accuracy |
|---|---|---|
| Cheng et al [9] / 2015 | Support Vector Machine Learning | 91.28% |
| Paul et al. [10] / 2017 | CNN | 91.43% |
| Afshar et al [11] / 2018 | Different Capsule network | 86.56% |
| Afshar et al [12] / 2019 | Additional inputs such as coarse tumour boundaries and Capsule Network | 90.89% |
| Phaye et al.[13] / 2018 | Capsule Networks by varying the feature maps in the CNN | 95.03% |
| Anaraki et al. [15] / 2019 | Optimised CNN | 94.2% |
| Swati et al. [16]/ 2019 | Transfer learned CNN | 94.82% |
| Ghassemi et al. [19] / 2020 | Transfer learned GAN | 95.6% |
| **Proposed** | • **Transfer learning approach using ResNet 50**<br>• **Manual feature Extraction and ML classifiers**<br>• **Hybrid Firefly optimised multi-class classifier** | **96 %**<br>**81 %**<br>**99 %** |

**Table 10: Related Works and Comparison**

## VI. CONCLUSION AND FUTURE ENHANCEMENT

We proposed three brand-new approaches for classifying MRI brain tumours utilising transfer learning on ResNet 50, manually selected features with ML classifiers and a hybrid framework for better diagnostic outcomes. The suggested transfer learning architecture using ResNet 50 performed feature extraction from the input tumour images. These characteristics and additional modules were utilised to categorise glioma, meningioma, and pituitary tumours, and the classification accuracy was 96%, which was the best. However, the hyperparameter tuning and training time is the main difficulty during the implementation of this model. This can be overcome with the second model, whilst the accuracy is less than the transfer learning model. In the third approach using a hybrid framework, the feature extraction is performed using ResNet 50 and the feature optimisation is done using ERT followed by the firefly swarm intelligence algorithm. The developed hybrid method attained the highest accuracy of 99% using the Figshare dataset. As an extended work in brain tumour classification, there are several potential directions for future research. These include integrating data from multiple imaging modalities, using deep learning models for tumour progress prediction, incorporating clinical data into classification models, and using transfer learning to improve the classification accuracy for smaller datasets.

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