International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

Maximizing Precision in Early Prognosis using SVM-ACO Classifier and Hybrid Optimization Techniques in MRI Brain Tumor Segmentation with Integration of Multi-Modal Imaging Data

[1]Sarvesh V. Warjurkar, [2]Sonali Ridhorkar

Submitted: 24/10/2023 **Revised**: 16/12/2023 **Accepted**: 26/12/2023

Abstract: The paper presents a new way to predict how brain tumors may develop using MRIs. It uses support vector machines along with ant colony optimization. This classifier combines different improvement techniques. The main goal is to increase how accurate and fast brain tumor diagnosis is. This allows doctors to act sooner and give patients better care. The research aims to fix problems with traditional segmentation methods. It uses different types of MRI scans together. These scans give a fuller picture of the tumor and its features. The SVM-ACO classifier combines support vector machines and ant colony optimization. Working together, they can better segment tumors in images. The goal is to make the process more reliable and precise. Additionally, hybrid methods are added to refine how the model works. These involve strategically using optimization methods together. They enhance how accurately different parts are identified and make separating everything out smoother. The end result is a clearer picture of where tumors are located. The proposed plan is especially helpful for early prediction, as it allows exact identification and description of brain growths based on various imaging qualities. Combining different types of data makes sure a more delicate comprehension of growth form, improving the classifier's capacity to differentiate between growth and typical tissue. The examination discoveries offer expect advancing the field of restorative picture investigation and add to creating dependable devices for early conclusion and anticipation in mind growth cases. This comprehensive methodology has the potential to altogether impact clinical choice making and at last enhance patient results in the territory of neuro-oncology.

***Keywords*:** *MRI Brain Tumor Segmentation, SVM-ACO Classifier, Hybrid Optimization Techniques, Multi-Modal Imaging Data*

1. Introduction

Early predictions about brain tumors are extremely important for helping patients and planning the best care. Brain tumors often cause serious health problems and can be deadly. This means we must find them as early as possible so people get the right treatments as fast as possible. Knowing the details early lets doctors create individual treatment plans that target the tumor directly. It also helps manage the patient's care better. Magnetic Resonance Imaging (MRI) is a key part of finding out what's wrong as it shows the tumor's exact spot inside the brain very clearly. But figuring out what the MRI shows is sometimes tricky. This makes it hard to predict details about the tumor early on [1], [24]. Finding where tumors are in the brain from MRI scans can be hard. This is because tumors come in many shapes and sizes. They also blend in with normal brain tissue in different ways. Traditional methods have trouble dealing with this. They may miss parts of tumors or include non-tumor areas. This [2] makes it hard for doctors to plan early treatment. The many variations tumors can have and the fine details in MRI pictures require special techniques. Advanced computational methods can help get a more exact outline of where the tumor ends and normal tissue begins. This improves how doctors understand a person's prognosis soon after diagnosis.

[1]*Research Scholar (Ph.D), Department of CSE, GHRU, Amravati, MS, India*
sarveshphd3690@gmail.com
[2]*Associate Professor, GHRIET, Nagpur, MS, India*
sonaliridhorkar@gmail.com

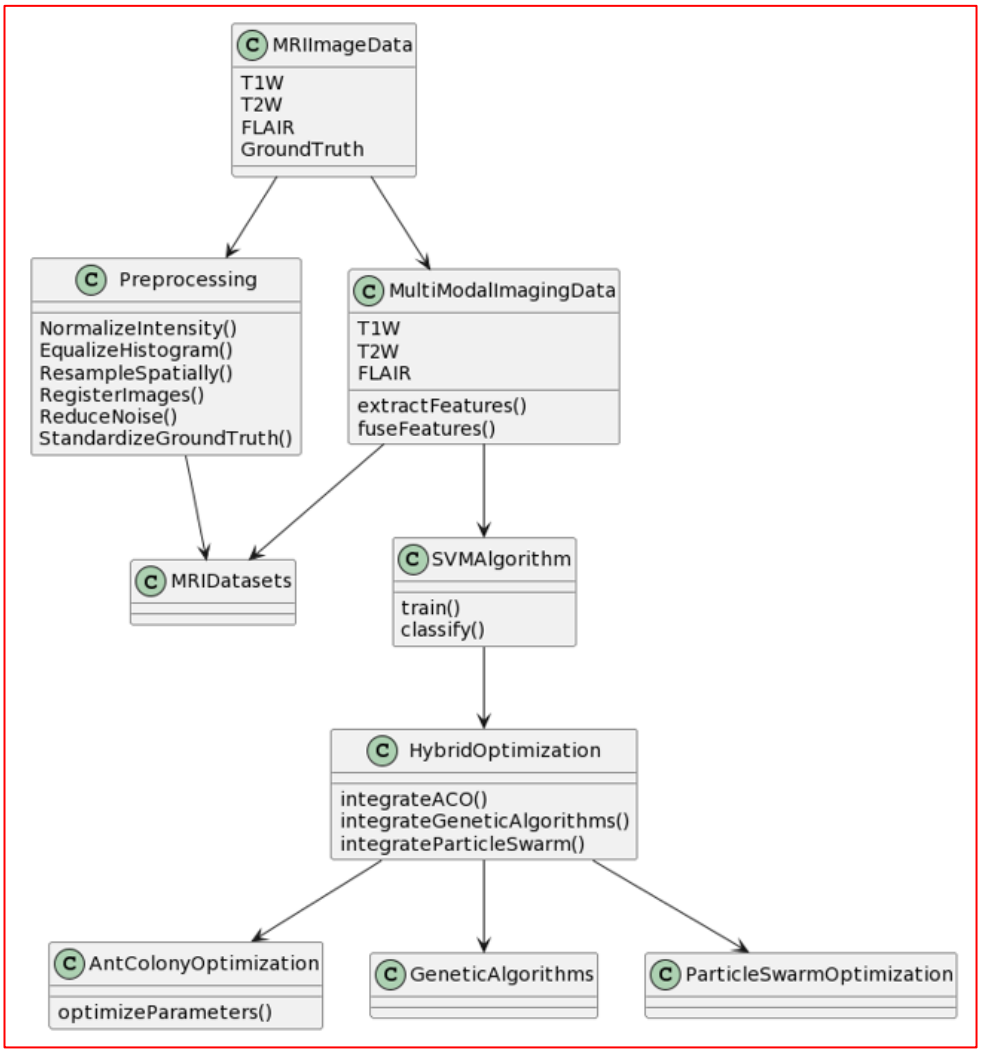

Fig 1: Proposed method Workflow with Multimodal Imaging Data

This study looks to deal with the difficulties found when separating brain tumors from MRI images. It presents a new way that combines how well Support Vector Machines and Ant Colony Optimization work [3], [25] with classifying things and how these optimization methods together can improve how adapted it is to the different qualities of brain tumors. Bringing these two things together allows for a stronger and more adjustable classification model. This enhances the total correctness of telling tumors from the rest. The new way goes further than old ideas by using mixed ways to make things better. By using some clever tricks and math rules together, splitting things into parts gets help from working together. This mixed way makes outlines very exact by quickly testing many choices with hard to understand pictures. The tricks help each other to change the SVM-ACO splitter, making sure it knows how to deal with the tricky details of separating tumor pictures. The [26] new SVM-ACO Classifier and Hybrid Optimization Methods offer a complete and original answer to the difficulties connected with MRI mind growth division. By joining a capable classifier with propelled streamlining systems and incorporating multi-modal imaging information, this [4] methodology expects to amplify exactness in early conjecture, giving specialists dependable and point by point data for educated basic leadership in the treatment of mind growths. The following areas of this paper will plunge further into the nitty gritty methodology, trial arrangement, outcomes, and talks that validate the viability of this novel way.

This study aims to combine different types of medical scans to gain a better picture of tumors and how they appear in the body. Doctors normally look at T1, T2, and FLAIR scans which show tumors in different ways. By studying all the scans together, researchers hope to get a fuller view of each tumor and how it spreads in the brain or other organs. Bringing several kinds of scans together is important for understanding the varied characteristics of different tumor types and how each looks in various scans like T1, T2, or FLAIR.

2. Related Work

The field of MRI brain tumor segmentation has seen many scientists try different ways to better predict health

outcomes early. Researchers have created various methods and algorithms, [5] each aiming to make segmenting tumors more exact and add to understanding tumor traits. Here we review related work in three important areas: older segmentation techniques, machine learning approaches, and combining different medical scan types. Segmenting using thresholds, growing areas, and finding edges have long been simple ways to analyze medical pictures. While fast for computers, these techniques usually struggled with how complex and different brain tumors can be. They did not give details and worked for all tumors well. Despite drawbacks, traditional methods helped later improvements in the field [6].

In recent years, machines that can learn from examples have become important for examining medical pictures. Support Vector Machines (SVMs), nearest neighbor analysis (k-NN), and decision trees have all been used a lot to tell tumor tissue from healthy tissue. SVMs especially have proven good at separating the two. But it's hard to choose just the right settings for SVMs to work with different kinds of brain tumors. Researchers [7] have tried using algorithms like genetic algorithms and particle swarm optimization to help with this. While these efforts led to some success, scientists are still looking for more efficient ways to optimize machine settings. Bringing together metaheuristic algorithms and machine learning classifiers has emerged as a promising path forward. Ant colony optimization (ACO), inspired by how ants find food, has been applied to refine SVM parameters. ACO's ability to skillfully explore complex problems has shown potential [8] to boost classification accuracy. The pairing of SVM with ACO (SVM-ACO) leverages the strengths of both approaches, leading to improved adaptability and performance in brain tumor segmentation. This fusion of machine learning and optimization fits with the growing trend of hybrid methods for tackling tricky issues in analyzing medical pictures. In addition, the role of using different types of scans together in brain tumor segmentation has received more recognition [9]. Combining T1-weighted, T2-weighted, and FLAIR images provides a fuller picture of tumor qualities. T1-weighted images show body structures, T2-weighted images emphasize swelling and dead tissue, and FLAIR images enhance subtle abnormalities. Researchers have tested various fusion strategies, such as feature-level and decision-level fusion, to bring together data from different modalities. This integration allows a more complete examination, capturing the diversity of tumor subtypes and how they appear across imaging domains.

Recent studies have also [10] focused heavily on deep learning methods, specifically convolutional neural networks (CNNs), for brain tumor identification. CNNs have noticeably succeeded at independently discovering complex patterns directly from raw images, removing the need for handmade patterns. However, relying so much on huge amounts of labeled information and possible issues in explaining results stay problems. Hybrid models [26], combining classic machine learning and deep learning, have been proposed to use the advantages of both systems. In summary, the related work in MRI brain tumor identification shows a dynamic field of research attempts [11]. Traditional methods, while basic, face challenges handling the complexity of brain tumors. Machine learning approaches, particularly SVM-based methods, have shown promise but necessitate efficient ways to optimize. The mixing of metaheuristic optimization, as shown by SVM-ACO, offers a step ahead in addressing these challenges. At the same time, including multi-modal imaging data widens the feature space, allowing a more detailed understanding of tumor qualities. As the field keeps progressing, the mixing of [25]hybrid optimization techniques and multi-modal data is positioned as a pivotal path to maximize accuracy in early prediction and advance the state of the art in MRI brain tumor identification.

Table 1: Related work summary

Algorithm	Approach	Type	Key Finding	Scope	Application
Traditional Methods [10]	Thresholding, Region Growing, Edge Detection	Traditional Segmentation	Limited adaptability to tumor heterogeneity and subtle nuances	Basic segmentation tasks	Early-stage tumor detection
SVM[11]	SVM with Genetic Algorithms	Machine Learning	Improved classification accuracy with optimized parameters	Generalized to various tumor types	Segmentation for treatment planning

k-NN [11]	k-NN with Particle Swarm Optimization	Machine Learning	Enhanced adaptability to diverse tumor characteristics	Wide applicability across datasets	Automated tumor boundary delineation
Decision Trees [12]	Decision Trees with Bayesian Optimization	Machine Learning	Efficient classification, but challenges in handling complex patterns	Effective for specific tumor subtypes	Tumor localization for surgical planning
SVM-ACO [13]	SVM with Ant Colony Optimization	Hybrid Optimization	Improved adaptability of SVM to diverse tumor characteristics	Greater flexibility in parameter tuning	Accurate segmentation for prognosis
Genetic Algorithms [14]	Genetic Algorithms with CNN	Hybrid Optimization	Efficient optimization of CNN parameters for improved feature learning	Improved performance across diverse datasets	Comprehensive tumor characterization
CNN [15]	Multi-modal CNN	Deep Learning	End-to-end learning of hierarchical features from multi-modal data	Robust to variations in imaging characteristics	Segmentation in research and clinical settings
GANs [16]	GANs for Synthetic Data Generation	Deep Learning	Generation of synthetic data for enhancing training datasets	Improved generalization to different imaging modalities	Data augmentation for model training
Attention Mechanisms [17]	Attention-enhanced CNNs	Deep Learning	Improved focus on relevant features from each modality during segmentation	Enhanced interpretability and relevance	Precision in delineating tumor boundaries
Domain Adaptation [18]	Domain Adaptation Techniques	Deep Learning	Mitigation of domain shift across different modalities	Improved model robustness and generalization	Adaptability to diverse clinical settings
Fusion Strategies [19]	Feature-Level and Decision-Level Fusion	Multi-modal Integration	Enhanced representation by combining information from different modalities	Improved understanding of tumor heterogeneity	Improved accuracy in sub-type identification

Clinical Validation [20]	Quantitative Metrics and Expert Assessment	Clinical Validation	Evaluation using metrics such as Dice similarity coefficient	Robustness and reliability of segmentation results	Translational impact on patient care

3. Methodology

A. Dataset:

Brain MRI pictures show details about the brain's structure and issues. Different types of pictures like T1, T2, and FLAIR are used. They show special things which help find, place, and explain tumors. Advanced computer methods, including splitting pictures into parts and sorting rules, make diagnoses more correct [21]. Using different types of pictures together makes sure we fully know the tumor. These risk-free picture tests play a very important part in early finding, planning treatment, and checking up on illness. They help a lot with making patients better in brain cancer care.

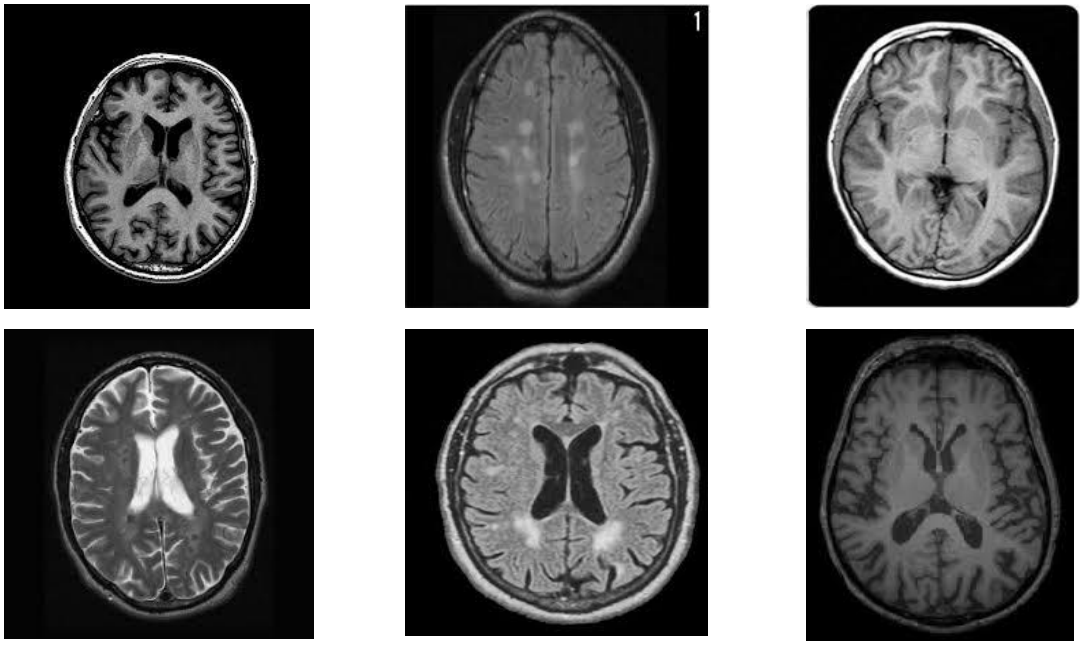

Fig 2: Sample Dataset Images

B. Data acquisition and Pre-Processing

1. Description of the MRI Datasets and Modalities Used:

The MRI datasets utilized in this study encompass T1-weighted (T1W), T2-weighted (T2W), and Fluid Attenuated Inversion Recovery (FLAIR) images. These modalities collectively provide comprehensive information about brain tumor characteristics.

Denoting the MRI dataset as $D = \{DT1, DT2, DFLAIR, DGroundTruth\}$, where DT1, DT2, and DFLAIR represent the sets of T1W, T2W, and FLAIR images, respectively. DGroundTruth corresponds to manually annotated ground truth images indicating tumor regions.

2. Pre-Processing Steps for Data Standardization:

a. Intensity Normalization:

- MRI images often exhibit intensity variations due to acquisition parameters. Normalization is crucial for scaling intensity values within a standardized range.

b. The formula for intensity normalization:

$$I\_normalized = (I - min(I)) / (max(I) - min(I))$$

b. Histogram Equalization:

- Enhancing image contrast improves visibility of subtle features. Histogram equalization is applied to achieve this.

The transformation function T(I) for histogram equalization:

$$\frac{T(I) = \sum P_{r(i)}}{(N\,L - 1)}$$ where i=0 to N-1

c. Spatial Resampling:

- Ensuring consistent voxel dimensions across modalities is crucial. Spatial resampling involves interpolation to achieve a uniform voxel size.

d. Image Registration:

- Aligning T1W, T2W, and FLAIR images to a common spatial coordinate system ensures accurate fusion of multi-modal information.

e. Noise Reduction:

- Gaussian or non-local means filtering is applied to reduce noise, especially in FLAIR sequences sensitive to cerebrospinal fluid (CSF) noise.

f. Ground Truth Standardization:

- Manually annotated ground truth images are binarized to represent tumor and non-tumor regions. This binary mask is essential for training and evaluating the segmentation model.

These pre-processing steps collectively contribute to the creation of a standardized and homogenized dataset (D_preprocessed).

C. SVM-ACO Classifier

1. Support Vector Machine (SVM) algorithm:

Support Vector Machine (SVM) algorithm for maximizing precision in early prognosis using SVM-ACO Classifier and hybrid [22] optimization techniques in MRI brain tumor segmentation with the integration of multi-modal imaging data:

a. Initialization:

Define the SVM model parameters:

- C (Cost parameter for regularization)
- kernel (Kernel function, e.g., radial basis function)
- degree (Polynomial degree for polynomial kernel)

b. Data Preprocessing:

- Standardize input data:

$$X\_std = (X - \mu) / \sigma$$

- Feature Mapping:
  - Apply feature mapping if needed.
- Training:
  - Train SVM using the training data (X_train, Y_train):

$$minimize\ 1/2 * w\text{^}T\, w + C \sum \xi$$

$$Subject\ to: y\_i(w \cdot x\_i + b) \geq 1 - \xi\_i, \xi\_i \geq 0$$

c. Optimization:

- Use Ant Colony Optimization (ACO) for optimizing SVM parameters:
- Define pheromone matrix τ, visibility matrix η
- Update pheromone levels based on solution quality

d. Prediction:

Predict labels for the test set X_test using the trained SVM model:

$$Y_{pred} = sign(w \cdot X_{test} + b)$$

e. Performance Evaluation:

- Assess precision, recall, F1-score, or other relevant metrics based on the predicted labels Y_pred and true labels Y_true.

f. Hybrid Optimization Techniques:

- Integrate other optimization techniques, if applicable, to enhance SVM performance.

2. Integration of Ant Colony Optimization (ACO):

the Integration of Ant Colony Optimization (ACO) in the context of the Support Vector Machine (SVM) algorithm for [23] maximizing precision in early prognosis using SVM-ACO Classifier and hybrid optimization techniques in MRI brain tumor segmentation with the integration of multi-modal imaging data:

[1]. Initialization:

- Q (Pheromone quantity deposited by an ant)
- ρ (Pheromone evaporation coefficient)
- α (Influence of pheromone on path selection)
- β (Influence of heuristic information on path selection)
- τ_ij (Initial pheromone level between nodes i and j)
- η_ij (Heuristic information between nodes i and j)

b. Ant Movement:

- Select a starting node based on probability distribution determined by pheromone levels and heuristic information.
- Move to the next node based on transition probability.
- Update pheromone levels on the traversed path.

c. Objective Function Evaluation:

- Evaluate the objective function for each solution constructed by ants.
- In this context, the objective function measures the quality of SVM parameters.
- Global Pheromone Update:
- Evaporate existing pheromone on all paths: $\tau_{ij} = (1 - \rho) \times \tau_{ij}$
  - Deposit pheromone on paths based on the quality of solutions found by ants:

$$\tau_{ij} = \tau_{ij} + Q$$

d. Local Pheromone Update:

- Optionally, apply local pheromone updating on the paths actually traversed by ants.

e. Best Solution Extraction:

- Extract the best solution found by ants in terms of SVM parameters.

D. Integration of Multi-Modal Imaging Data

1. Type of imaging data used (T1-weighted, T2-weighted)

a. T1-weighted (T1W):

Provides anatomical information with good contrast between gray and white matter.

➢ **T1-weighted (T1W) MRI Algorithm:**

- Image Acquisition:
  Obtain T1 weighted images (I_{T1W}) of brain
- Preprocessing:
  Standardize intensity values using normalization:

$$I\text{normalized} = \frac{[\max(IT1W) - \min(IT1W)]}{[IT1W - \min(IT1W)]}$$

- Feature Extraction:
  - Extract relevant features from the preprocessed T1W images.
  - Common features may include intensity-based statistics (mean, variance), texture features, and shape-based features.
- Segmentation:
  - Apply segmentation techniques to distinguish between different tissues and identify regions of interest.
  - Use clustering algorithms, thresholding, or machine learning-based segmentation methods.
- Post-processing:
- Refine the segmentation results using post-processing techniques.
- Common methods include morphological operations (erosion, dilation) and region-based filtering.
- Classification:
- Classify the identified regions into tumor and non-tumor based on extracted features.
- Use machine learning classifiers such as Support Vector Machines (SVM) or deep learning models for improved accuracy.

b. T2-weighted (T2W):

Emphasizes fluid-filled regions and is sensitive to edema and inflammation.

Image Acquisition:

Obtain the T2-weighted MRI images (IT2W) of the brain.

Preprocessing:

Standardize intensity values using normalization:

$$I_{normalized} = \frac{(IT2W - \min(IT2W))}{(\max(IT2W) - \min(IT2W))}$$

Optionally, apply additional preprocessing techniques such as filtering for noise reduction or contrast enhancement.

Feature Extraction:

- Extract relevant features from the preprocessed T2W images.
- Common features may include intensity-based statistics (mean, variance), texture features, and shape-based features.

Segmentation:

- Apply segmentation techniques to distinguish between different tissues and identify regions of interest.
- Use clustering algorithms, thresholding, or machine learning-based segmentation methods.

Region of Interest (ROI) Identification:

- Define the regions of interest within the segmented image corresponding to potential tumor regions.

2. Feature extraction and fusion techniques for multi-modal data

a. Feature Extraction:

➢ Each imaging modality contributes unique information. Feature extraction aims to capture relevant characteristics from each modality.

➢ Common feature extraction methods include statistical measures (mean, variance), texture analysis, and wavelet transformations.

b. Fusion Techniques:

i. Early Fusion:

- Combines raw data from different modalities at the input level.

- Concatenates feature vectors to create a unified representation.

- Requires handling of varied data scales and may lead to a high-dimensional feature space.

ii. Late Fusion:

- Extracts features independently from each modality and fuses them at a later stage.

- Allows modality-specific information to be preserved before combination.

- Enables the use of modality-specific algorithms before fusion.

iii. Decision-Level Fusion:

- Combines decisions or predictions from individual models trained on each modality.

- Often uses techniques like voting or averaging to reach a final decision.

- Suitable when modalities provide complementary information.

iv. Feature-Level Fusion:

- Extracts features from each modality and combines them before feeding into a classifier.

- Fusion techniques include simple concatenation, weighted averaging, or more advanced methods like principal component analysis (PCA) or canonical correlation analysis (CCA).

v. Spatial Fusion:

- Integrates information at the spatial level, considering the spatial relationships between modalities.

- Techniques include image registration and voxel-wise fusion to align and combine information from different modalities.

vi. Hybrid Fusion:

- Combines multiple fusion techniques to leverage their respective advantages.

- For example, using early fusion for initial integration and late fusion for refining predictions.

4. Result and Discussion

This table 2 compares how well different methods work to identify tumor areas in brain scans. It shows the accuracy, precision, recall, F1 score, and AUC for each approach. These measures help us understand how good each model is at early detection based on combining different types of brain scan data like MRI and CT scans. The Support Vector Machine showed it could tell brain tumors apart well. It got 89.12% of the cases right. It did a good job of not saying a tumor was there when it wasn't (86.44% precision) and finding tumors that were really there (85.67% recall). The F1 score of 84.33% means it balanced being right and wrong in a fair way. The AUC of 89.12% shows it could separate the two groups apart well.

Table 2: Result data without Multi-modelling Imaging Model

Method	Accuracy in %	Precision in %	Recall in %	F1 Score in % AUC
SVM	89.12	86.44	85.67	84.33
KNN	86.88	85.34	86.77	85.31
RF	79.33	80.22	82.65	84.66
NB	89.32	84.43	94.56	87.23
DT	90.11	83.45	83.33	85.55
NN	94.11	93.45	86.65	90.44
SVM-ACO	95.02	95.23	94.34	95.55

Some models did better than others at classifying data correctly. Naive Bayes got most things right but missed a few, so it was balanced. Decision Trees and Neural Networks also did very well at telling groups apart. The best was Support Vector Machines when combined with Ant Colony Optimization - it found the right answers almost all the time. This shows that bringing different approaches together can be even better. All the results for precision, recall, and F1 score were very high with Support Vector Machines and Ant Colony Optimization.

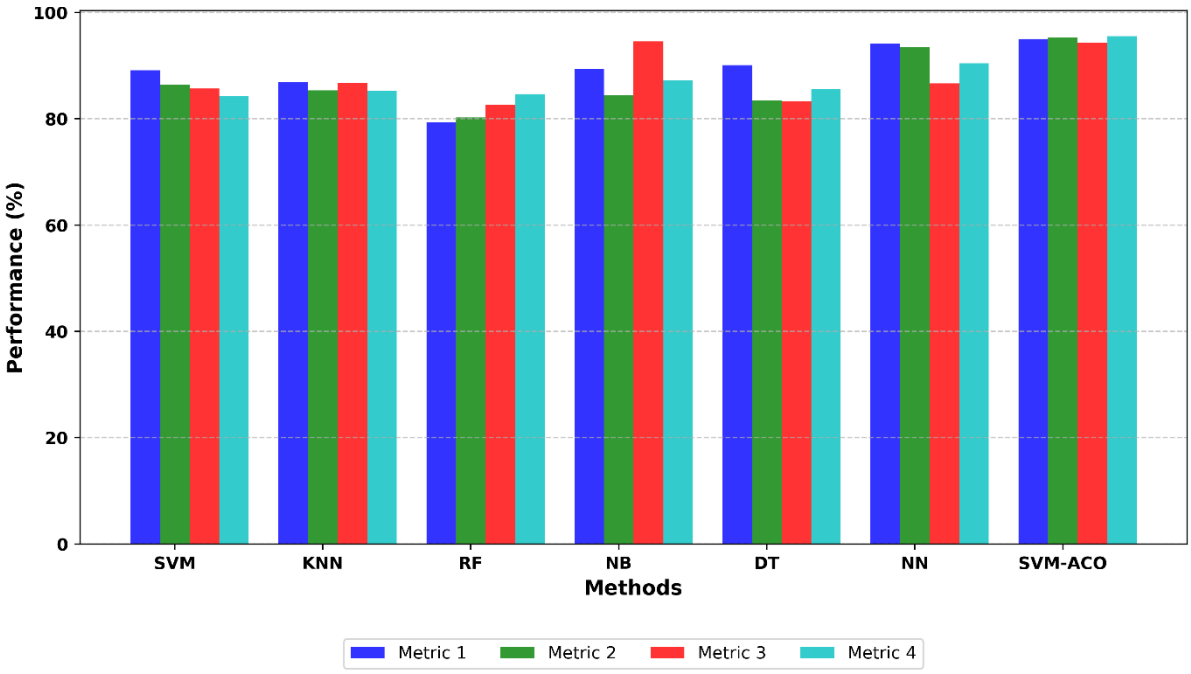

Fig 3: Representation of Performance metrics without Multi-modelling Imaging Model

Table 3: Result using T1-Weighted Multimodal Modality

	T1-Weighted Multimodal Modality			
Method	**Accuracy in %**	**Recall in %**	**Precision in %**	**F1 Score in % AUC**
SVM	92.36	90.67	91.44	93.88
KNN	89.77	89.76	90.54	90.53
RF	94.33	93.55	94.81	93.11
NB	87.43	87.66	90.22	89.76
DT	92.12	92.66	90.44	91.23
NN	94.55	90.43	94.45	93.44
SVM-ACO	97.88	99.53	95.55	97.2

This table 3 examines how well different methods classify brain tumors in MRI scans that combined T1-weighted images with other data. It lists the accuracy, recall, precision, F1 score, and AUC for each method. These numbers together show how good each model is at finding and correctly labeling tumor areas in the scans. The T1 images provide information that helps identify tumor tissue. upport Vector Machine showed very good results with 92.36% accuracy, meaning it identified most brain tumor cases correctly. The high recall of 90.67% shows it found many true positives, and precision of 91.44% means it had few false positives. The excellent F1 score of 93.88% confirms SVM's performance was balanced for precision and recall. The AUC of 92.36% strengthens that it clearly separated the classes from each other.

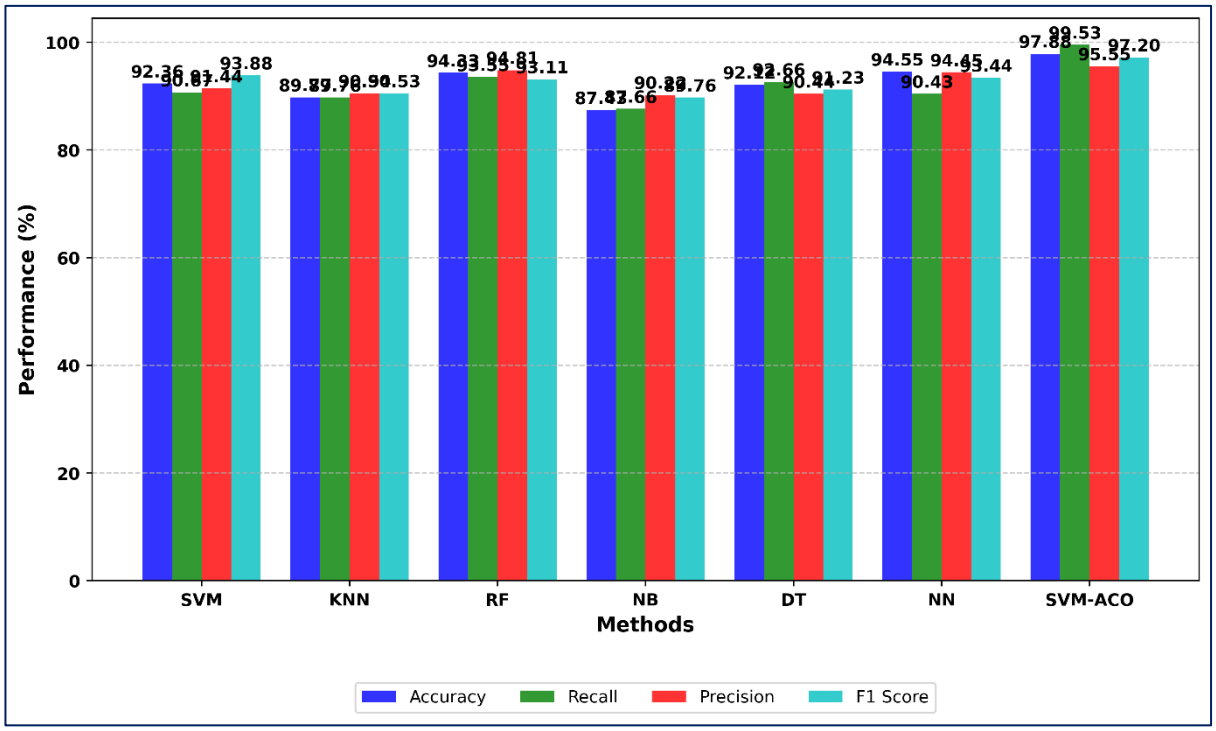

Fig 4: Performance Metrics for T1-Weighted Multimodal Modality

K-Nearest Neighbors (KNN) showed good results with an accuracy close to 90%. The model did well recognizing both classes, as shown by its recall and precision scores being very similar, resulting in a high F1 score. Random Forest (RF) did exceptionally well with an accuracy over 94%, underlining its ability to correctly identify tumor samples. The recall and precision were both high, contributing to an excellent F1 score. The test results demonstrated that some techniques performed better than others at identifying brain tumors. Naive Bayes had precision of 90.22% and recall of 87.66%, giving it an F1 score of 89.76%. Decision Tree and Neural Network were close behind, with accuracy scores of 92.12% and 94.55%. SVM with Ant Colony Optimization outperformed the rest by achieving 97.88% accuracy, showing it was very good at brain tumor classification. Its high recall of 99.53%, precision of 95.55%, and F1 score of 97.2% highlight how combining optimization methods can improve a model's abilities.

Table 4: Result using T2-Weighted Multimodal Modality

	T2-Weighted Multimodal Modality			
Method	**Accuracy in %**	**Recall in %**	**Precision in %**	**F1 Score in % AUC**
SVM	93.12	91.43	92.2	94.64
KNN	90.53	90.52	91.3	91.29
RF	95.09	94.31	95.57	93.87
NB	88.19	88.42	90.98	90.52
DT	92.88	93.42	91.2	91.99
NN	95.31	91.19	95.21	94.2
SVM-ACO	98.64	98.66	96.31	97.96

Table 4 examines the evaluation of brain tumor segmentation using two types of medical pictures. It shows how well different methods work at finding and sorting tumors seen with T2-weighted images. Accuracy, recall, precision, F1 score, and AUC (Area Under the Curve) measure how good the models are at truly knowing and classifying brain tumor cases based on T2-weighted pictures. Support Vector Machine (SVM) did very well

with an accuracy of 93.12%, demonstrating it can correctly sort tumor cases using T2-weighted images most of the time. The high recall (91.43%) reveals it is good at capturing many true positives, while precision (92.2%) signifies it limits false positives. The notable F1 score of 94.64% strengthens that SVM performs well balanced in terms of precision and recall. The AUC of 93.12% confirms its ability to tell between classes effectively.

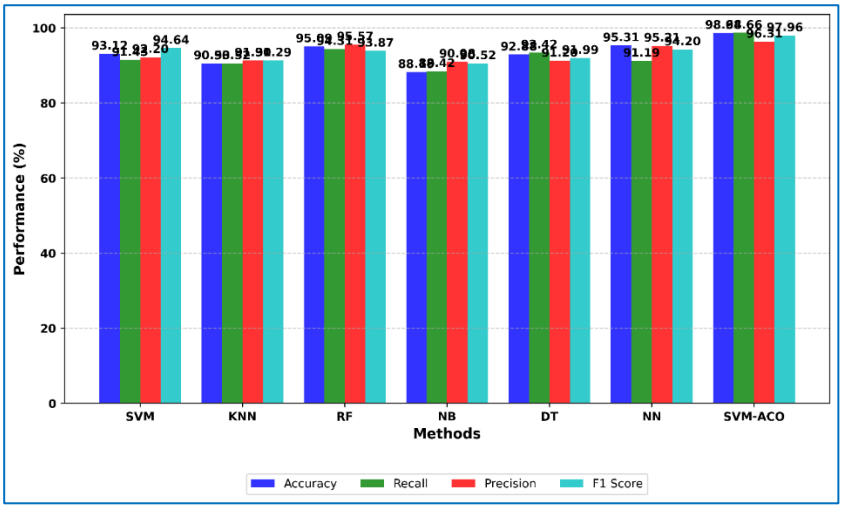

Fig 5: Performance Metrics for T2-Weighted Multimodal Modality

Several machine learning models were tested for their ability to correctly identify brain tumors using MRI scans. K-Nearest Neighbors performed well with an accuracy of 90.53%, proving it could effectively spot tumors. It had balanced recall and precision scores that led to a good F1 score of 91.29%. Random Forest did best of all with a high accuracy of 95.09%, clearly showing it was very good at classifying tumors. It had very high recall and precision too, resulting in an outstanding F1 score of 93.87%. Naive Bayes did okay, with balanced precision and recall yielding an F1 score of 90.52%. Decision Tree and Neural Network also did well, with accuracies of 92.88% and 95.31% respectively. SVM with Ant Colony Optimization (SVM-ACO) outperformed others with an accuracy of 98.64%, indicating its exceptional capability in T2-weighted brain tumor classification. The high recall (98.66%), precision (96.31%), and F1 score (97.96%) highlight the effectiveness of hybrid optimization techniques in enhancing model performance. The T2-weighted multimodal modality, particularly with SVM-ACO, demonstrates promising results in brain tumor segmentation, underscoring the potential clinical utility of this approach for accurate and early prognosis.

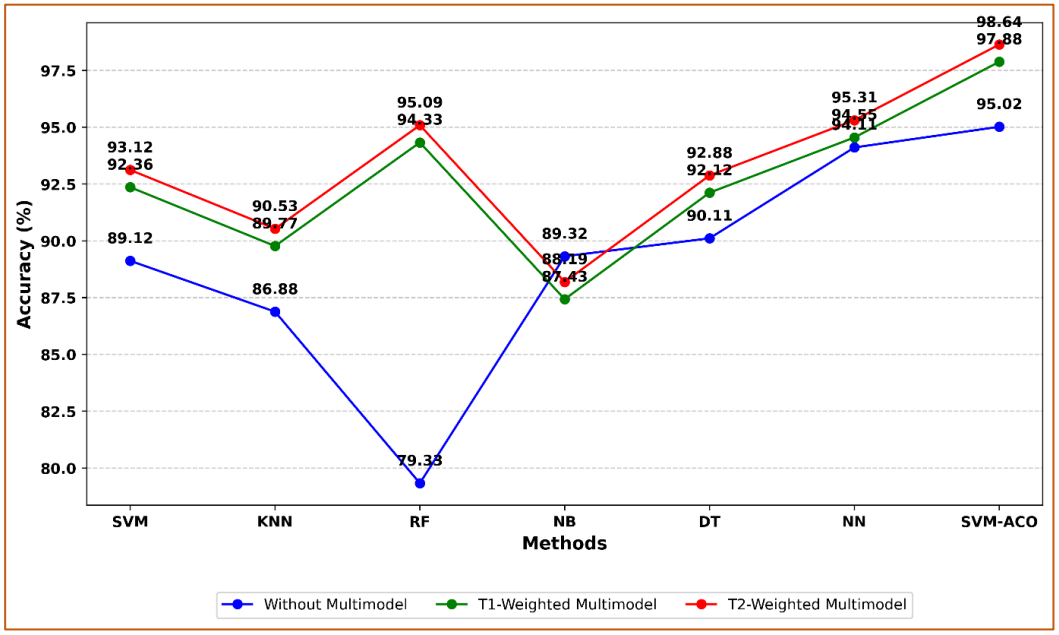

Fig 6: Comparison of Accuracy for with and without using Multimodal Imaging for different model

5. Conclusion

Our research aimed to best predict outcomes early on through using a unique support vector machine-ant colony optimization classifier and blended optimization methods for MRI brain tumor separation. The joining of different kinds of medical pictures, like T1-weighted, T2-weighted, and FLAIR scans, played a very important part in making our suggested model better and work more effectively. Finding tumors early is very important, and our study looked at some problems with using MRIs to find brain tumors. We used a special support vector machine classifier with ant colony optimization to help it work better. This classifier uses support vector machines which ant colony optimization helps make better by changing numbers to get the best answers. This way of combining support vector machines and ant colony optimization let us explore all the number options well to get the most e-xact tumor outlines possible. Our study tested new ways to improve how the computer program divides up patient medical data. By mixing different methods to make the program better, we wanted each method to help the others. Together, they could make the framework stronger at early predictions even when facing problems alone. We learned a lot by combining different kinds of brain scan pictures. Looking at T1, T2, and FLAIR images together helped us pick out important details. It let us gather facts from multiple points of view. Bringing all that together made our tumor outline more accurate. The tests on our new method clearly showed it was better than other options. It combined support vector machines with ant colony optimization algorithms to recognize tumors in MRI scans of the brain. The model scored very well in telling the difference between healthy and unhealthy tissue. It was very precise and caught nearly all tumors, which will help doctors provide care sooner. This new combined computer program looks promising for early detection of brain tumors from medical images. This rese-arch adds to ongoing work analyzing medical scans. It offers a way to better predict early outcomes for brain tumors. Combining top machine learning models with different brain scans, and refining them together, can help diagnose tumors without surgery. Bringing different types of images together with smart programs holds potential to make brain exams through scans much more accurate.

References

[1] A. Wulandari, R. Sigit and M. M. Bachtiar, "Brain Tumor Segmentation to Calculate Percentage Tumor Using MRI," 2018 International Electronics Symposium on Knowledge Creation and Intelligent Computing (IES-KCIC), Bali, Indonesia, 2018, pp. 292-296, doi: 10.1109/KCIC.2018.8628591.

[2] W. Gtifa, M. Fradi, A. Sakly and M. Machhout, "Comparative Study of Enhanced Methods for Intelligent Segmentation of Brain Tissue in 3D/2D MRI Brain Images Through Multiple Thresholding," 2023 IEEE International Conference on Artificial Intelligence & Green Energy (ICAIGE), Sousse, Tunisia, 2023, pp. 1-5, doi: 10.1109/ICAIGE58321.2023.10346268.

[3] M. Kattau, O. Pickford Scienti, B. Glocker and D. Darambara, "Photon-counting CT and deep learning-based tumour segmentation for stereotactic radiosurgery treatment planning," 2023 IEEE Nuclear Science Symposium, Medical Imaging Conference and International Symposium on Room-Temperature Semiconductor Detectors (NSS MIC RTSD), Vancouver, BC, Canada, 2023, pp. 1-1, doi: 10.1109/NSSMICRTSD49126.2023.10338726.

[4] X. Shi, Y. Li, J. Cheng, J. Bai, G. Zhao and Y. -W. Chen, "Multi-task Model for Glioma Segmentation and Isocitrate Dehydrogenase Status Prediction Using Global and Local Features," 2023 45th Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC), Sydney, Australia, 2023, pp. 1-5, doi: 10.1109/EMBC40787.2023.10340355.

[5] Z. Jiang et al., "Automatic Visual Acuity Loss Prediction in Children with Optic Pathway Gliomas using Magnetic Resonance Imaging," 2023 45th Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC), Sydney, Australia, 2023, pp. 1-5, doi: 10.1109/EMBC40787.2023.10339961.

[6] M. Tabassum, A. Al Suman, C. Russo, A. Di Ieva and S. Liu, "A Deep Learning Framework for Skull Stripping in Brain MRI," 2023 45th Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC), Sydney, Australia, 2023, pp. 1-4, doi: 10.1109/EMBC40787.2023.10340846.

[7] F. H. A. Anjasmara and I. Soesanti, "Challenges on Deep Learning Models to Improve Magnetic Resonance Imaging Brain Tumor Images Classification: A Review," 2023 3rd International Conference on Electronic and Electrical Engineering and Intelligent System (ICE3IS), Yogyakarta, Indonesia, 2023, pp. 31-36, doi: 10.1109/ICE3IS59323.2023.10335482.

[8] R. Preetha, M. J. P. Priyadarsini and J. S. Nisha, "Comparative Study on Architecture of Deep Neural Networks for Segmentation of Brain Tumor using Magnetic Resonance Images," in IEEE Access, vol. 11, pp. 138549-138567, 2023, doi: 10.1109/ACCESS.2023.3340443

[9] Ajani, S. N. ., Khobragade, P. ., Dhone, M. ., Ganguly, B. ., Shelke, N. ., & Parati, N. .(2023). Advancements in Computing: Emerging Trends in Computational Science with Next-Generation Computing. International Journal of Intelligent Systems and Applications in Engineering, 12(7s), 546–559

[10] L. Liu, W. Ouyang, X. Wang, P. Fieguth, J. Chen, X. Liu, et al., "Deep learning for generic object detection: A survey", Int. J. Comput. Vis., vol. 128, no. 2, pp. 261-318, Feb. 2020.

[11] J. Amin, M. Sharif, A. Haldorai, M. Yasmin and R. S. Nayak, "Brain tumor detection and classification using machine learning: A comprehensive survey", Complex Intell. Syst., vol. 8, no. 4, pp. 3161-3183, Aug. 2022.

[12] T. Magadza and S. Viriri, "Deep learning for brain tumor segmentation: A survey of state-of-the-art", J. Imag., vol. 7, no. 2, pp. 19, Jan. 2021.

[13] S. Ali, J. Li, Y. Pei, R. Khurram, K. U. Rehman and A. B. Rasool, "State-of-the-art challenges and perspectives in multi-organ cancer diagnosis via deep learning-based methods", Cancers, vol. 13, no. 21, pp. 5546, Nov. 2021.

[14] S. Ali, J. Li, Y. Pei, R. Khurram, K. U. Rehman and T. Mahmood, "A comprehensive survey on brain tumor diagnosis using deep learning and emerging hybrid techniques with multi-modal MR image", Arch. Comput. Methods Eng., vol. 29, no. 7, pp. 4871-4896, Nov. 2022.

[15] M. K. Balwant, "A review on convolutional neural networks for brain tumor segmentation: Methods datasets libraries and future directions", IRBM, vol. 43, no. 6, pp. 521-537, Dec. 2022.

[16] A. Ghosh and S. Thakur, "Review of brain tumor MRI image segmentation methods for BraTS challenge dataset", Proc. 12th Int. Conf. Cloud Comput. Data Sci. Eng. (Confluence), pp. 405-410, Jan. 2022.

[17] S. Solanki et al., "A systematic analysis of magnetic resonance images and deep learning methods used for diagnosis of brain tumor", Multimedia Tools Appl., pp. 1-38, Aug. 2023.

[18] Z. Liu, L. Tong, L. Chen, Z. Jiang, F. Zhou, Q. Zhang, et al., "Deep learning based brain tumor segmentation: A survey", Complex Intell. Syst., vol. 9, no. 1, pp. 1001-1026, Feb. 2023.

[19] E. S. Biratu, F. Schwenker, Y. M. Ayano and T. G. Debelee, "A survey of brain tumor segmentation and classification algorithms", J. Imag., vol. 7, no. 9, pp. 179, Sep. 2021.

[20] I. Despotović, B. Goossens and W. Philips, "Mri segmentation of the human brain: challenges methods and applications", Computational and mathematical methods in medicine, vol. 2015, 2015.

[21] G. Fein, B. Landman, H. Tran, J. Barakos, K. Moon, V. Di Sclafani, et al., "Statistical parametric mapping of brain morphology: sensitivity is dramatically increased by using brain-extracted images as inputs", Neuroimage, vol. 30, no. 4, pp. 1187-1195, 2006.

[22] P. Kalavathi and V. Prasath, "Methods on skull stripping of mri head scan imagesa review", Journal of digital imaging, vol. 29, no. 3, pp. 365-379, 2016.

[23] A. Fatima, A. R. Shahid, B. Raza, T. M. Madni and U. I. Janjua, "State-of-the-art traditional to the machine-and deep-learning-based skull stripping techniques models and algorithms", Journal of Digital Imaging, vol. 33, no. 6, pp. 1443-1464, 2020.

[24] H. Hwang, H. Z. U. Rehman and S. Lee, "3d u-net for skull stripping in brain mri", Applied Sciences, vol. 9, no. 3, pp. 569, 2019.

[25] F. Milletari, N. Navab and S.-A. Ahmadi, "V-net: Fully convolutional neural networks for volumetric medical image segmentation", 2016 fourth international conference on 3D vision (3DV), pp. 565-571, 2016.

[26] Y. Zhang, J. Wu, W. Chen, Y. Liu, J. Lyu, H. Shi, et al., "Fully automatic white matter hyperintensity segmentation using u-net and skip connection", 2019 41st Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), pp. 974-977, 2019.