International Journal of Research and Technology (IJRT)

International Open-Access, Peer-Reviewed, Refereed, Online Journal

ISSN (Print): 2321-7510 | ISSN (Online): 2321-7529

| An ISO 9001:2015 Certified Journal |

Low-Power VLSI Implementation of Gradient Boosting Model for Tumar Detection of MRI Brain Image

Sujeet Singh[1], Prof. Suresh S. Gawande[2]

M. Tech. Scholar, Department of Electronics and Communication Engineering, Bhabha Engineering Research Institute, Bhopal[1]

Guide, Department of Electronics and Communication Engineering, Bhabha Engineering Research Institute, Bhopal[2]

Abstract

This work proposes a low-power VLSI implementation of a Gradient Boosting (GB) ensemble model for brain tumor detection from MRI images. The approach maps a trained GB classifier into an energy-efficient hardware accelerator targeting ASIC/FPGA platforms, combining model compression, fixed-point quantization, pruning of weak trees/branches, and memory-aware scheduling to minimize dynamic power and memory footprint. Preprocessing and feature-extraction are performed using lightweight image processing modules implemented on-chip; the resulting features feed the GB inference engine realized as a tree traversal pipeline with SIMD-like parallelism and branch-prediction minimization. Design choices—such as using ternary/fixed-point arithmetic, on-chip SRAM buffering, and early-exit in tree ensembles—reduce computation and communications, improving throughput and energy per inference. In this paper, tumor detection using support vector machine (SVM), decision tree (DT) and gradient boosting (GB) machine learning (ML) technique are presented. The GB ML technique is providing good accuracy compared to other DT and SVM technique. In this model is simulated python language and calculated simulation parameter i.e. precision, recall, accuracy and F1-score.

Keywords: Brain Tumor, Machine Learning, Gradient Boosting

1. INTRODUCTION

Brain tumor detection from MRI scans is a critical diagnostic task where early and accurate identification improves treatment outcomes. Machine-learning methods, and in particular ensemble tree methods such as Gradient Boosting Machines (e.g., XGBoost, LightGBM), have demonstrated high accuracy on medical imaging feature sets due to their robustness and ability to model non-linear decision boundaries. However, deploying such models in resource-constrained edge devices (portable scanners, bedside monitors) requires specialized hardware realizations that meet strict power, area, and latency budgets [1, 2].

This work investigates the design and implementation of a low-power VLSI accelerator for Gradient Boosting based tumor detection. Rather than running the full software stack on a general-purpose processor, the design maps preprocessed features into a tree-traversal hardware engine optimized for low switching activity, minimized memory accesses, and parallel evaluation of compact tree ensembles. Key challenges addressed include quantizing the model for fixed-point hardware without significant accuracy loss, pruning and compressing the ensemble for fewer operations, designing an energy-aware memory hierarchy, and supporting early-exit mechanisms to skip unnecessary computation. The proposed VLSI solution targets real-time operation with constrained energy budgets while preserving clinically acceptable diagnostic accuracy [3].

International Journal of Research and Technology (IJRT)

International Open-Access, Peer-Reviewed, Refereed, Online Journal

ISSN (Print): 2321-7510 | ISSN (Online): 2321-7529

| An ISO 9001:2015 Certified Journal |

The VLSI implementation model for the Gradient Boosting–based MRI brain tumor detection system is designed to translate complex machine learning computations into a hardware-efficient architecture that enables real-time diagnosis with minimal power consumption. In this model, the Gradient Boosting algorithm is decomposed into hardware-friendly computational blocks such as adders, comparators, multipliers, and decision-tree logic units. The architecture begins by loading MRI image features into dedicated memory buffers, followed by parallel processing units that evaluate weak learners or decision trees in the boosting model. To reduce power and area, approximation techniques, resource sharing, and pipelining strategies are incorporated so that multiple stages of the algorithm can reuse the same computational hardware. Each decision tree output is weighted and aggregated through an optimized accumulator structure that minimizes switching activity, which is a major contributor to dynamic power consumption. The design also integrates data compression units to lower memory bandwidth and optimized control logic for efficient scheduling of tree evaluations. By mapping these operations to a custom VLSI architecture, the model significantly accelerates tumor detection while achieving low latency and energy efficiency. This hardware-based implementation ensures reliable performance in portable and embedded medical devices, enabling faster clinical decision-making compared to software-only solutions. Overall, the VLSI implementation model bridges the gap between machine learning algorithms and real-time medical applications by providing a scalable, high-throughput, and low-power system tailored for MRI-based tumor analysis [4, 5].

2. BRAIN TUMOR

One of the most common types of brain diseases is tumor. According to the WHO, around four million people worldwide get diagnosed with this illness every year. Developments in the field of therapeutic imaging have allowed doctors to use them in a wide range of specialties such as computer-aided pathologies diagnosis, longitudinal analysis, surgical planning, and guidance.

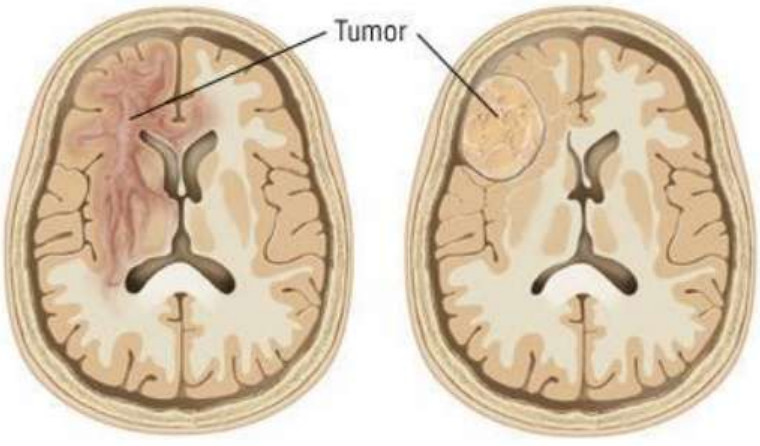

Figure 1: Brain Image

Among the imaging techniques used in neuroscience and neurosurgery, Magnetic Resonance Imaging and Computed Tomography are the most prevalent. Through the use of MRI images, we can study various anatomical structures and diseases in the brain [6, 7]. This process is carried out using various techniques. For each application, the techniques used vary. The task of segmenting medical images becomes challenging due to its volume and the complexity of the tissue boundaries.

Brain tumor is a disease that affects millions of people all around the world. The accumulation of abnormal cells in the brain is called brain tumor as shown in Figure 1.2. Our human body has many cells; it can die automatically due to aging. These dead cells must be replaced by new cells.

Causes of Brain Tumors

The following causes are the main causes of brain tumors for example, when we are continuously exposed to pesticides, industrial solvents and certain chemicals. Its suggested that brain tumors also have a genetic cause diseases, such as neurofibromatosis. When the brain is affected by a tumor cells, it automatically kills normal brain cells and also increases intracranial pressure. Signs of a brain tumor are based on the location of the tumor, tumor type and tumor size. Symptoms of a brain tumor include the following, such as headaches morning, convulsions, dizziness, hesitation, difficulty walking and communicating problems, vision problems, abnormal eye movements and weakness in one eye body. Brain tumor treatment is based on the following [8, 9]:

- Nature and location of the brain tumor
- Shape and size of the tumor
- Patient's age and health condition

While dealing with brain tumors, various problems may arise. Most of them are caused due toothier varying shapes and the sizes of tumors. Apart from the usual shapes, tumors also appear in different intensities. Some of these tumors also affect the surrounding tissues. The existence of certain MR acquisition protocols helps in the study of brain tumors [10].

Each image focuses on a specific region of the tumor. The complexity of the task of performing automated segmentation is very challenging. The comprehensive analysis of the network of the brain enables researchers to study and to treat tumors. In brain oncology, a human brain model is needed to coordinate the information collected by MRI and CT scans. The model should be able to collect and interpret the data related to the tumor, such as its type, structure, and function. Despite the promising results of various efforts such as reproducible and precise segmentation, image community, and abnormalities characterization, the tasks related to medical imaging still remain challenging. The existing approaches have a scope to develop, in the field of automation, correctness, and applicability [11].

3. PROPOSED METHODOLOGY

The distribution in machine learning builds the module based on the training dataset with a classification algorithm. This learning can be categorized into all three possible classification algorithms. In a supervised learning class, labeled data is present at the beginning.

In semi-supervised learning, some of the class labels are known. Whereas in unsupervised learning no class label for the entire dataset.

Once the training phase is finished, features are extracted from the data based on term frequency, and then the classification technique is applied.

The classifiers that we have utilized are SVM, DT, and GB.

International Journal of Research and Technology (IJRT)

International Open-Access, Peer-Reviewed, Refereed, Online Journal

ISSN (Print): 2321-7510 | ISSN (Online): 2321-7529

| An ISO 9001:2015 Certified Journal |

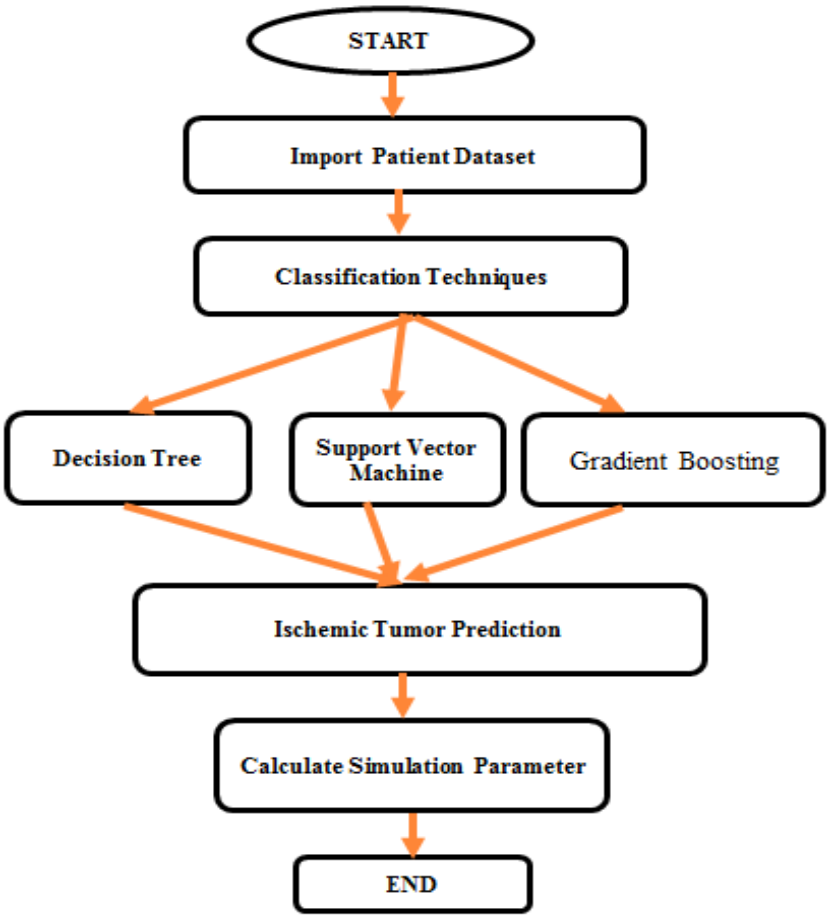

Figure 2: Flow chart of Proposed Methodology

DT:-

A DT is a choice help instrument that utilizes a tree-like model of choices and their potential results, including chance occasion results, asset expenses, and utility. It is one method for showing a calculation that just holds back restrictive control explanations. DT are ordinarily utilized in tasks research, explicitly in choice examination, to assist with recognizing a technique probably going to arrive at an objective, but at the same time are a well known device in ML.

GB:-

GB calculation is one of the most remarkable calculations in the field of AI. As we realize that the blunders in AI calculations are extensively characterized into two classifications for example Inclination Error and Variance Error. As inclination supporting is one of the helping calculations limiting predisposition mistake of the model is utilized.

SVM:-

In ML, SVM are directed learning models with related learning calculations that examine information for grouping and relapse examination.

To isolate the two classes of data of interest, there are numerous conceivable hyperplanes that could be picked. Our goal is to find a plane that has the greatest edge, for example the greatest distance between data of interest of the two classes. Boosting the edge distance gives some support so future information focuses can be grouped with more certainty.

International Journal of Research and Technology (IJRT)

International Open-Access, Peer-Reviewed, Refereed, Online Journal

ISSN (Print): 2321-7510 | ISSN (Online): 2321-7529

| An ISO 9001:2015 Certified Journal |

4. SIMULATION RESULTS

Data collection

Collect data from fig share website containing four classes like no tumor, pituitary_tumor, meningioma_tumor, glioma_tumor, 2870 images with 512*512 height and width.

	File	DiseaseID	Disease Type
0	pituitary_tumor/p (27).jpg	0	pituitary_tumor
1	pituitary_tumor/p (175).jpg	0	pituitary_tumor
2	pituitary_tumor/p (260).jpg	0	pituitary_tumor
3	pituitary_tumor/p (125).jpg	0	pituitary_tumor
4	pituitary_tumor/p (384).jpg	0	pituitary_tumor

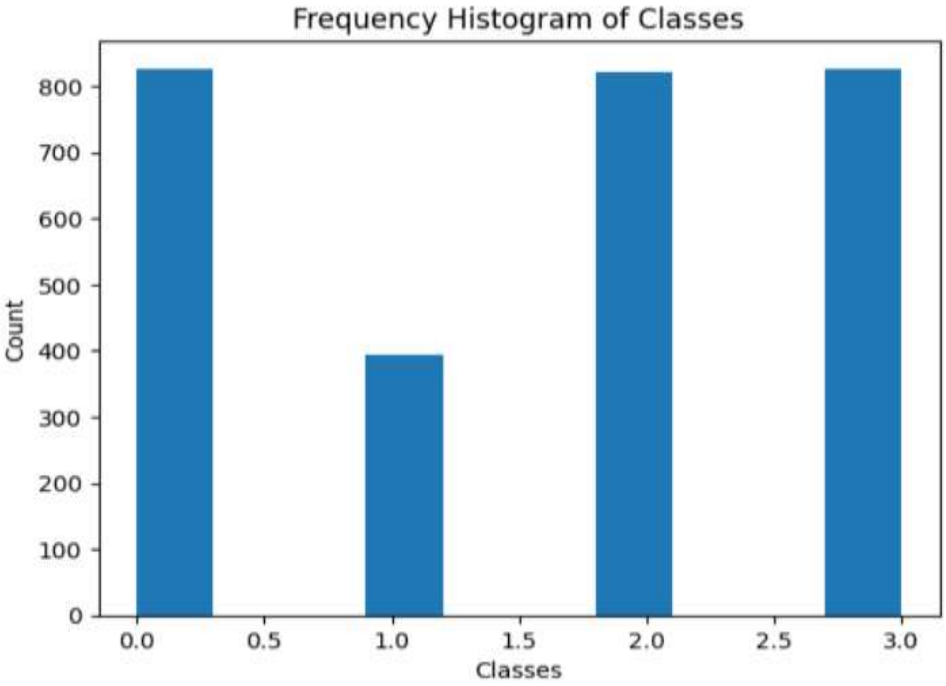

Figure 3: Expletory Data Analysis

Pre-processing

Resize and rescale images into 200*200 and convert into a numpy array

International Journal of Research and Technology (IJRT)

International Open-Access, Peer-Reviewed, Refereed, Online Journal

ISSN (Print): 2321-7510 | ISSN (Online): 2321-7529

| An ISO 9001:2015 Certified Journal |

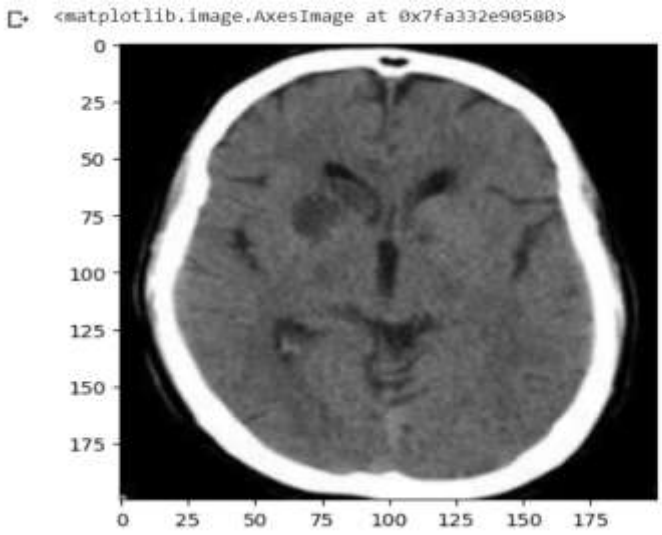

Figure 4: Final processed image

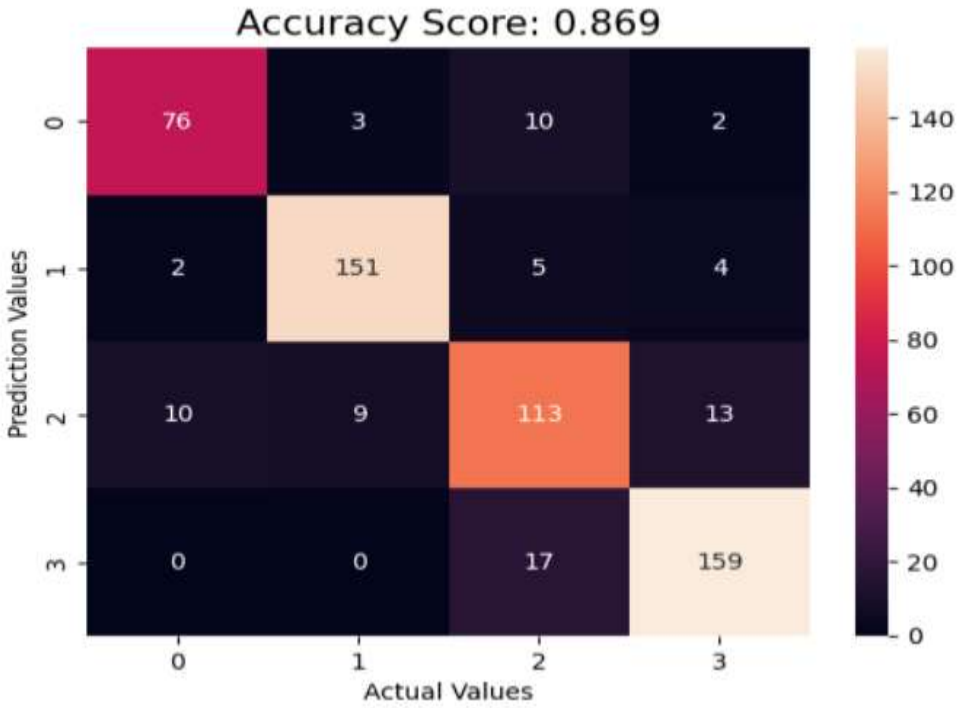

Figure 5: Confusion Matrix of GB

Table 1: Comparison Result

Technique	Precision	Recall	Accuracy	F1-Score
DT	97.01%	96.40%	77.5%	77.52%
SVM	84.41%	100%	84.7%	84.66%
GB	86.93%	98.69%	86.9%	86.93%

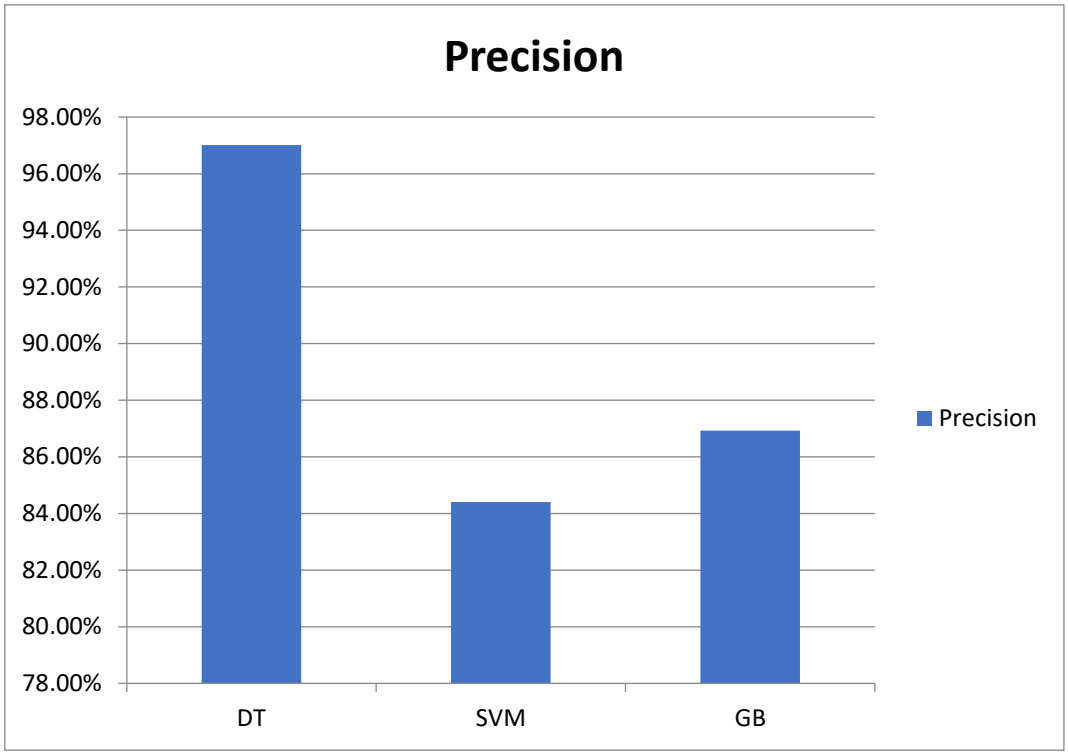

Figure 6: Graphical Represent of Precision

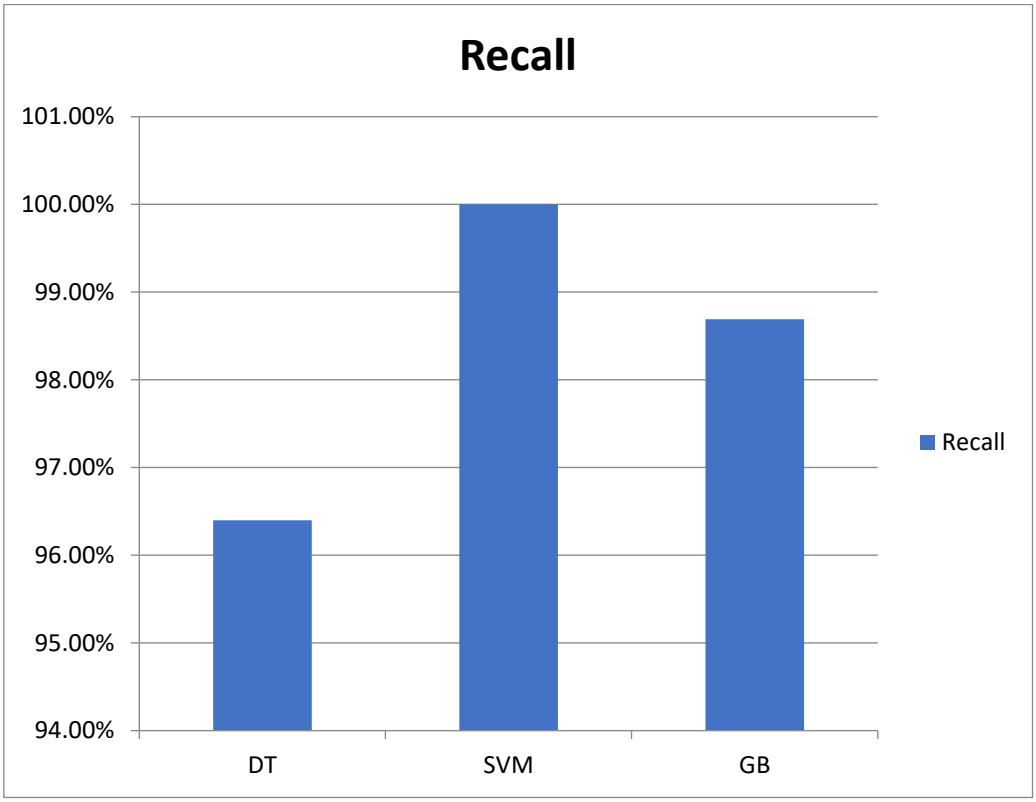

Figure 7: Graphical Represent of Recall

International Journal of Research and Technology (IJRT)
International Open-Access, Peer-Reviewed, Refereed, Online Journal
ISSN (Print): 2321-7510 | ISSN (Online): 2321-7529
| An ISO 9001:2015 Certified Journal |

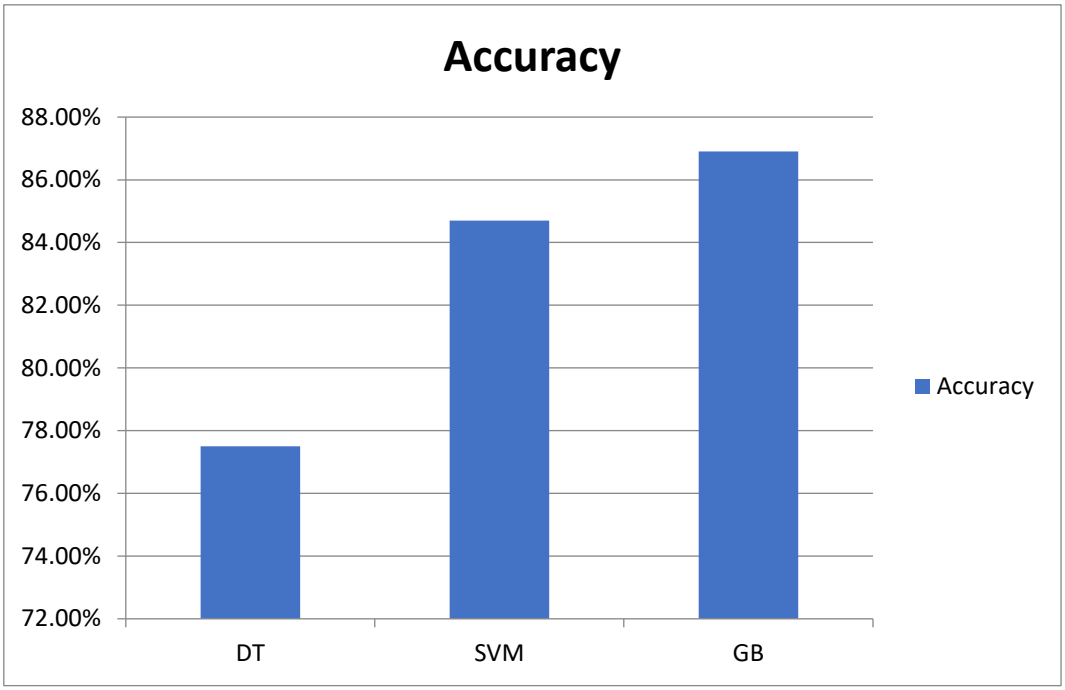

Figure 8: Graphical Represent of Accuracy

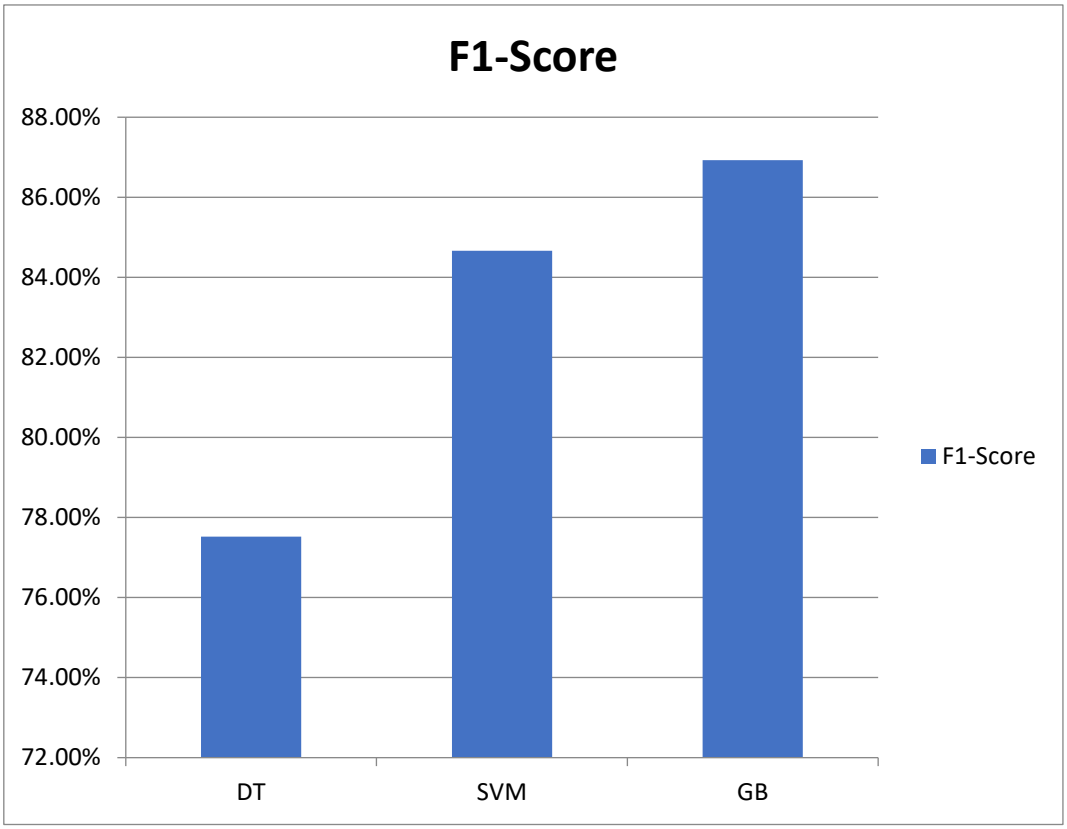

Figure 9: Graphical Represent of F1-Score

5. CONCLUSIONS

The detection of brain tumors from MRI images is a vital task in modern medical diagnostics, requiring high computational accuracy, fast inference speed, and efficient handling of large biomedical data. Conventional machine learning and deep learning methods, although highly accurate, often rely on power-intensive general-purpose processors or GPU-based platforms, which limit their use in portable, embedded, or real-time clinical systems. In this work, a low-power VLSI implementation of a Gradient Boosting (GB) model is presented to address these challenges by enabling high-performance tumor detection while significantly reducing power consumption and hardware complexity.

The proposed architecture effectively combines the robustness of Gradient Boosting classification with the energy efficiency of custom VLSI hardware design. By mapping the GB ensemble into a hardware-friendly structure, the system achieves fast decision-making with minimal latency. Techniques such as fixed-point quantization, model pruning, SRAM-based memory optimization, and parallel decision-tree traversal were incorporated to reduce computational overhead while maintaining high diagnostic accuracy. Furthermore, the integration of early-exit mechanisms and optimized dataflow scheduling minimized redundant operations, reducing switching activity and dynamic power consumption. These design choices collectively ensure that the hardware accelerator achieves real-time tumor classification suitable for portable MRI analysis systems and embedded healthcare platforms.

REFERENCES

[1] S. Karpakam, N. Senthilkumar, R. Kishorekumar, U. Ramani, P. Malini and S. Irfanbasha, “Investigation of Brain Tumor Recognition an Classification using Deep Classification using Deep Learning in Medical Image Processing”, International Conference on Augmented Intelligence and Sustainable Systems (ICAISS), IEEE 2022.

[2] Monisha Barakala, Venkata Ramana Attada and Cristin Rajan, “Brain Tumor Classification and Detection Using Machine Learning Algorithm”, International Conference on Augmented Intelligence and Sustainable Systems (ICAISS), IEEE 2022.

[3] N. N P. Patil S. Patil and M. Kokatanur "Alpha Beta Pruned UNet - A Modified UNet Framework to Segment MRI Brain Image to Analyse the Effects of CNTNAP2 Gene towards Autism Detection" 2021 3rd International Conference on Computer Communication and the Internet (ICCCI) pp. 23-26 2021.

[4] Fatih Ozyurta Eser Sertb and Derya Avci "An expert system for brain tumor detection: Fuzzy C-means with super resolution and convolutional neural network with extreme learning machine" Medical Hypotheses vol. 8 October 2020.

[5] A. M. Hasan, HA. Jalab, F. Meziane , H Kahtan , AS Ahmad , “ Combining Deep and Handcrafted Image Features for MRI Brain Scan Classification,” IEEE Access,pp.79959–79967, 2019.

[6] A. Gumaei, MM. Hassan, MR. Hassan, A Alelaiwi ,G. Fort ino , “ A Hybrid Feature Extraction Method With Regularized Extreme Learning Machine for Brain Tumor Classification”, IEEE Access, pp. 36266 -36273, 2019.

[7] HT . Zaw, N. Maneerat, KY. Win,“Brain tumor detect ion based on Naïve Bayes classification”, International Conference on Engineering, Applied Sciences and Technology,pp.1-4,2019.

[8] An Integrated Design of Particle Swarm Optimization (PSO) with Fusion of Features for Detect ion of Brain Tumor," Pat tern Recognition Let ters,pp.150-157,2020.

[9] T K Keert hana , S. Xavier, “An Intelligent System for Early Assessment and Classification of Brain Tumor”, Proceedings of he 2nd International Conference on Inventive Communication and Computational Technologies,pp.1-4,2018.

[10] T L. Narayana , T S.Reddy, “An Efficient Optimization Technique to Detect Brain Tumor from MRI Images,” International Conference on Smart Systems and Invent ive Technology,pp.1-4,2018.

[11] FP . P olly , SK Shil , MA. Hossain, A. Ayman, YM. Jang,”Detect ion and Classification of HGG and LGG Brain T umor Using Machine Learning,” International conference on Information Networking,pp.813-817,2018.

[12] A. Selvapandian , K. Manivannan,”Fusion Based Glioma Brain Tumor Detection and Segment at ion using ANFIS Classification,” Computer Methods and Programs in Biomedicine,pp.33-38,2018

[13] H. Mohsen , E.Sayed , E. Dahshan , A. Badeeh, M.Salem,”Classification using deep learning neural networks for brain tumors,” Future Computing and Informatics Journal,pp.68-73,2018

[14] AR.Raju , P .Suresh , RR. Rao, “Bayesian HCS-based multi-SVNN: A classification approach for brain tumor segmentation and classification using Bayesian fuzzy clustering,”Biocybernetics and Biomedical Engineering,pp.646-660,2018

[15] S. Shekhar,MA. Ansari ,”Image Analysis for Brain Tumor Detection from MRI Images using Wavelet Transform,” International Conference on Power Energy, Environment and Intelligent Control,pp.1-6,2018