International Journal of Advanced Research and Multidisciplinary Trends (IJARMT)
An International Open Access, Peer-Reviewed Refereed Journal
Impact Factor: 6.4 Website: https://ijarmt.com ISSN No.: 3048-9458

Review Paper on VLSI Implementation of Tumor Detection using Machine Learning Technique

Sujeet Singh
M. Tech. Scholar
Department of Electronics and Communication Engineering
Bhabha Engineering Research Institute, Bhopal
Prof. Suresh S. Gawande
Guide
Department of Electronics and Communication Engineering
Bhabha Engineering Research Institute, Bhopal

Abstract
The rapid growth of medical imaging technologies has led to an increasing demand for fast, accurate, and energy-efficient tumor detection systems. Machine Learning (ML) and Deep Learning (DL) models have shown exceptional performance in classifying and detecting tumors in modalities such as MRI, CT, and PET. However, software-based implementations often require high computational resources, making them unsuitable for real-time and portable healthcare devices. To address this challenge, researchers are moving toward Very-Large-Scale Integration (VLSI) implementations of ML-based tumor detection algorithms. This review paper presents a comprehensive analysis of recent advancements in VLSI architectures designed for tumor detection using ML techniques. It highlights various hardware-optimized models such as Support Vector Machines, Convolutional Neural Networks, Gradient Boosting Machines, Decision Trees, and hybrid ML–VLSI systems. Key design parameters including power consumption, hardware complexity, latency, memory usage, and scalability are systematically reviewed. Furthermore, the paper discusses architectural optimization strategies such as pipelining, parallelism, quantization, approximate computing, and multiplier-less design approaches to achieve low-power operation. Finally, open research challenges and future directions are identified, emphasizing the need for high-accuracy, low-power ML hardware capable of supporting next-generation point-of-care medical diagnostic systems.

Keywords: - Machine Learning, Tumor Detection, VLSI Implementation

1. INTRODUCTION

Tumor detection in medical imaging has gained major importance due to the rising number of cancer cases worldwide and the increasing dependency on imaging modalities such as Magnetic Resonance Imaging (MRI), Computed Tomography (CT), and ultrasound for early diagnosis. Traditional manual inspection of medical images by radiologists is time-consuming, subjective, and prone to human error, particularly when dealing with small, complex, or low-contrast tumors. As a result, Machine Learning (ML) and Deep Learning (DL) techniques have emerged as powerful tools for automating tumor detection and supporting clinical decision-making. Models such as Convolutional Neural Networks (CNN), Support Vector Machines (SVM), Random Forests, Decision Trees, k-Means clustering, and Gradient Boosting Machines have shown high accuracy in detecting abnormalities in brain, lung, breast, liver, and other organs. However, these ML algorithms typically operate in software environments that rely on high-performance CPUs or GPUs, which are expensive, power-intensive, and unsuitable for portable or real-time medical devices [1, 2].

To overcome these limitations, researchers are increasingly exploring Very-Large-Scale Integration (VLSI) based implementations of ML models. VLSI design allows computationally intensive ML algorithms to be mapped into hardware, enabling faster processing speeds, parallel computation, and significantly reduced power consumption compared to traditional software systems. Hardware accelerators designed using CMOS, FPGA, or ASIC technologies provide dedicated architectures for image feature extraction, classification, and segmentation tasks, making them highly suitable for real-time tumor detection applications [3, 4].

The integration of ML with VLSI focuses on designing hardware-efficient processing units capable of handling large amounts of imaging data with minimal energy usage. Various architecture-level optimization techniques are applied, including pipelined data paths, parallel computing, multiplier-less arithmetic, quantization, approximate computing, and memory access reduction strategies. Such optimizations make ML-based tumor detection systems feasible for use in wearable health monitoring devices, point-of-care diagnostic equipment, and low-power embedded systems deployed in remote or resource-constrained environments.

Multiple studies have proposed hardware acceleration for ML algorithms. For example, CNN-based tumor detection models have been implemented on FPGAs using parallel convolution engines and reduced-precision arithmetic to achieve high throughput. SVM and Decision Tree classifiers have been mapped to ASICs with efficient comparison units and linear decision boundaries, offering high classification accuracy at low cost. Gradient Boosting algorithms have also been explored for VLSI implementation using optimized tree traversal hardware and low-power aggregation units. These models significantly improve the processing speed of tumor detection while maintaining high accuracy [5].

Despite substantial progress, challenges remain in designing hardware that supports complex ML models with millions of parameters. Memory consumption, feature dimensionality, non-linear operations, and the need for flexible model updates pose significant constraints on VLSI architectures. Moreover, balancing the trade-offs between accuracy, power consumption, hardware complexity, and silicon area remains an ongoing research problem.

This review paper summarizes state-of-the-art VLSI implementations of ML algorithms for tumor detection, evaluates the performance of different architectures, and highlights recent innovations that make hardware-based medical imaging more practical and reliable. The paper also identifies research gaps and future challenges, aiming to support further advancements in high-speed, low-energy ML hardware for next-generation medical diagnostics [6, 7].

2. LITERATURE REVIEW

S. Karpakam et al. [1], a mind cancer is the development of synapses that are strange, some of which might advance into disease. The most common method for detecting brain tumors is a magnetic resonance imaging (MRI) scan. The cerebrum's strange tissue development should be visible on the X-ray pictures, which uncover. Profound learning and AI strategies are utilized to distinguish cerebrum growths in various exploration distributions. It just takes an exceptionally short measure of time to foresee a mind cancer when these calculations are applied to X-ray pictures, and the expanded precision simplifies patient therapy. The radiologist is able to quickly make decisions thanks to these forecasts. Deep learning, a convolution neural network (CNN), an artificial neural network (ANN), a self-defined neural network, and the existence of a brain tumor are utilized in the proposed strategy.

Monisha Barakala et al. [2], the humanoid system's most important component is the human brain. Mind cancers are brought about by cells that develop and isolate in the cerebrum in manners that shouldn't. As mind cancers develop, they can transform into cerebrum disease. PC vision is vital to human wellbeing since it removes the requirement for individuals to pursue precise choices. The most common and safest ways to get an image using magnetic resonance imaging (MRI) are CT scans, X-rays, and MRI scans. Small things can be found using MRI. We want to discuss the various ways that brain MRI can be used to find brain cancer in our paper. In this study, we removed noises from an MR image prior to processing with the bilateral filter (BF). The binary thresholding and Convolution Neural Network (CNN) segmentation methods were then used to locate the tumor region. Training datasets, test datasets, and validation datasets are all available. Our machine will be able to determine whether or not the subject has a brain tumor. A few proportions of execution, like exactness, responsiveness, and particularity, will be utilized to check the outcomes out. These thick layers separate highlights and all elements are passed to a completely associated layer. Brain MRI features are extracted more effectively by dense networks. Because MRI provides additional details about the structure and functions of cells, this work is conducted using MRI. It is hoped that the proposed work will perform better than other works of a similar nature.

N. N P. Patil et al. [3], the idea behind the proposed work is to use image segmentation to automatically detect autism. CNN is the most remarkable strategy for biomedical picture division where a few variations are proposed. The modified UNet segmentation method for image segmentation and classification known as Alpha-Beta Pruned UNet, which is a UNet dimensionality reduction technique, is the primary focus of the proposed work. Along with the results of the experiments, a metric is also used to compare UNet and the proposed algorithm.

Fatih Ozyurta et al. [4], one of the recent hot topics is super-resolution, which raises the resolution of images to new heights. A brain magnetic resonance image (MRI)'s important information is made more visible and clear by increasing the image's resolution in terms of the information it contains. As a result, the associated image's tumor borders will be more easily identified. Brain tumor detection using super-resolution convolutional neural networks and extreme learning machine algorithms (SR-FCM-CNN) has been proposed in this study. Using the Super Resolution Fuzzy-C-Means (SR-FCM) method for tumor detection from brain MR images, this study aimed to efficiently segment tumors. Following that, extreme learning machine (ELM) classification and feature extraction using the pretrained SqueezeNet architecture from convolutional neural network (CNN) architectures were carried out. In the trial studies, it has been resolved that mind cancers have been exceptional divided and eliminated utilizing SR-FCM technique. A smaller, with fewer parameters, neural network model was used to extract features using the SqueezeeNet architecture. Using SR-FCM, a diagnosis of segmented brain tumors has been made with an accuracy rate of 98.33% using the proposed approach. This rate is more prominent 10% than the pace of acknowledgment of mind growths portioned with fluffy C-implies (FCM) without SR.

A. M. Hasan et al. [5], advances in the space of man-made reasoning, AI, and clinical imaging innovations have permitted the improvement of the clinical picture handling field for certain shocking outcomes over the most recent twenty years. These developments empowered the clinicians to see the human body in high-goal or three-layered cross-sectional cuts, which brought about an expansion in the precision of the conclusion and the assessment of patients in a harmless way. The ability of magnetic resonance imaging (MRI) brain scan classifiers to extract meaningful features is the fundamental step. Accordingly, many works have proposed various strategies for highlights extraction to order the unusual developments in the mind X-ray examines. In recent times, the application of deep learning algorithms to medical imaging has resulted in remarkable performance gains in the classification and diagnosis of complex pathologies like brain tumors. In this paper, a profound learning highlight extraction calculation is proposed to extricate the pertinent elements from X-ray mind examines. The modified gray level co-occurrence matrix (MGLCM) method is used to extract handcrafted features simultaneously. The support vector machine (SVM) is used as a classifier to enhance the MRI brain scan classification process by combining the extracted relevant features with handcrafted features. The acquired outcomes demonstrated that the mix of the profound learning approach and the high quality elements removed by MGLCM works on the precision of grouping of the SVM classifier up to 99.30%.

A. Gumaei et al. [6], classification of brain cancer is an essential step that relies on the physician's expertise and knowledge. In order to assist physicians and radiologists in identifying brain tumors, an automated tumor classification system is absolutely necessary. However, for appropriate treatments, the accuracy of current systems needs to be improved. In order to develop a method for accurately classifying brain tumors, we present a hybrid feature extraction and regularized extreme learning machine (RELM) approach. Preprocessing the brain images with a min-max normalization rule to increase contrast between brain regions and edges is the first step in this strategy. The features of the brain tumor are then extracted using a hybrid feature extraction strategy. Last but not least, a RELM is used to classify the kind of brain tumor. To assess and look at the proposed approach, a bunch of trials is directed on another public dataset of cerebrum pictures. The experiment's performance in terms of classification accuracy improved from 91.51 percent to 94.233% for the random holdout technique experiment, demonstrating that the method is more effective than the current state-of-the-art methods.

HT. Zaw et al. [7], mind malignant growth is brought about by the number of inhabitants in strange cells called glial cells that happens in the cerebrum. A worldwide health issue, the prevalence of brain cancer has been rising in tandem with the aging population over time. This paper aims to develop a method for identifying cancer-affected brain tissues, particularly Glioblastoma multiforme (GBM), a grade-4 tumor. GBM is one of the most dangerous types of brain cancer because it grows quickly and is more likely to spread to other brain regions. In this paper, Guileless Bayes grouping is used for acknowledgment of a growth locale precisely that contains all spreading destructive tissues. This study makes use of the Naive Bayes classifier-based prediction algorithm, a brain MRI database, preprocessing, morphological operations, pixel subtraction, maximum entropy threshold, statistical features extraction, and others. Using a variety of brain MRI images, this method seeks to identify the tumor area and determine whether or not it is a tumor. When contrasted with different strategies, this strategy can appropriately recognize the growth situated in various districts of the cerebrum including the center area (lined up with eye level) which is the critical benefit of this technique. At the point when tried on 50 X-ray pictures, this strategy creates 81.25% discovery rate on growth pictures and 100 percent recognition rate on non-cancer pictures with the general precision 94%.

In ref. [8], growth in mind is a significant reason for death in people. It has a high risk of developing cancer if it is not treated promptly and appropriately. As a result, early detection of brain tumors is a crucial requirement. In the beginning of this work, the brain surface extraction (BSE) method is used to remove the skull. The skull eliminated picture is then taken care of to molecule swarm advancement (PSO) to accomplish better division. Local binary patterns (LBP) and deep features of segmented images are extracted in the subsequent step, and a genetic algorithm (GA) is used to select the best features. Finally, the tumor grades are categorized using an artificial neural network (ANN) and other classifiers. The method is evaluated using the publicly available complex brain datasets RIDER and BRATS 2018 Challenge, which achieved maximum accuracy of 99 percent. The outcomes are likewise contrasted and existing strategies which apparent that the introduced strategy gave further developed results which are obvious evidence of its viability and oddity.

Problem Identification:-

- One of the most crucial tasks in any brain tumor detection system is the isolation of abnormal tissues from normal brain tissues.
- Interestingly, domain of brain tumor analysis has effectively utilized the concepts of medical image processing, particularly on MR images, to automate the core steps, i.e. extraction, segmentation, classification for proximate detection of tumor.

The past works of many researchers under medical image processing and soft computing have made noteworthy review analysis on automatic brain tumor detection techniques focusing segmentation as well as classification and their combinations.

3. BRAIN TUMOR USING MACHINE LEARNING

The malignant and benign are two main categories of the brain tumor. The skull is pressurized to enlarge from inside in case of growth of any benign or malignant tumor. This tumor leads to cerebrum lesion and that could be dangerous to existence also. The brain tumor is divided into two kinds - primary or secondary. The tumor which happens in the cerebrum is known as primary brain cancer. Various gray matters are gentle. An optional cerebrum tumor is additionally metastatic mind tumor. This tumor starts because of spreading of disease cells spread in the cerebral matter as of an additional limb in which lung or bosom is included. The encephalon could start inside the brain or it spread to from the rest of the organs of anatomy. It can broaden to the cerebrum. The growth rate and the position of a brain tumor investigate its impacts on the function of nervous system. The kind of brain tumor and also its size and location have assisted in prescribing the treatment options of brain tumor.

Machine Learning

Machine Learning is a subset of Artificial Intelligence concerned with “teaching” computers how to act without being explicitly programmed for every possible scenario. The central concept in

Machine Learning is developing algorithms that can self-learn by training on a massive number of inputs. Machine learning algorithms are used in various applications, such as email filtering and computer vision, where it is difficult or infeasible to develop conventional algorithms to perform the needed tasks [4]. Machine learning enables the analysis of vast amounts of information. While it usually delivers faster, more precise results to identify profitable prospects or dangerous risks, it may also require additional time and assets to train it appropriately. Merging machine learning with AI and perceptive technologies can make it even more effective in processing vast volumes of information. Machine learning is closely associated with computational statistics, which focuses on making predictions using computers. Machine learning approaches are conventionally divided into three broad categories, namely Supervised Learning, Unsupervised Learning & Semi-supervised Learning, depending on the nature of the "signal" or "feedback" available to the learning system.

Face anti-spoofing (FAS) has lately attracted increasing attention due to its vital role in securing face recognition systems from presentation attacks (PAs). As more and more realistic PAs with novel types spring up, traditional FAS methods based on handcrafted features become unreliable due to their limited representation capacity. With the emergence of large-scale academic datasets in the recent decade, machine learning based FAS achieve remarkable performance and dominate this area.

Supervised Learning

A model is trained through a process of learning in which predictions must be made and corrected if those predictions are wrong. The training process continues until a desired degree of accuracy is reached on the training data. Input data is called training data and has a known spam / not-spam label or result at one time.

Unsupervised Learning

By deducting the structures present in the input data, a model is prepared. This may be for general rules to be extracted. It may be through a mathematical process that redundancy can be systematically reduced, or similar data can be organized. There is no labeling of input data, and there is no known result.

Semi-Supervised Learning

Semi-supervised learning fell between unsupervised learning (without any labeled training data) and supervised learning (with completely labeled training data). There is a desired problem of prediction, but the model needs to learn the structures and make predictions to organize the data. Input data is a combination of instances that are marked and unlabeled.

4. VLSI IMPLEMENTATION

VLSI implementation plays a crucial role in transforming complex machine learning algorithms into practical, high-performance hardware suitable for real-time tumor detection. In this approach, the computational steps of an ML model—such as feature extraction, convolution operations, activation functions, and classification—are mapped directly onto specialized hardware blocks designed using CMOS, FPGA, or ASIC technologies. This hardware-based realization enables massive parallel processing, reduced latency, and significantly lower power consumption compared to software running on CPUs or GPUs. VLSI architectures often employ optimization techniques such as pipelining, parallelism, approximate computing, low-bit quantization, and multiplier-less arithmetic to minimize silicon area and memory usage while maintaining high accuracy. By integrating these architectural enhancements, VLSI-based ML accelerators become highly efficient, making them suitable for portable medical devices, embedded diagnostic systems, and point-of-care applications. Overall, VLSI implementation provides a compact, energy-efficient, and fast hardware platform capable of supporting advanced tumor detection models in real-world healthcare settings.

5. CONCLUSION

VLSI-based implementation of machine learning techniques for tumor detection represents a transformative step toward achieving real-time, low-power, and portable medical imaging systems. Through the review of existing research, it is evident that mapping ML algorithms to hardware significantly enhances detection speed, reduces power consumption, and enables deployment in constrained healthcare environments. Techniques such as pipelining, parallelism, quantization, and approximate computing have played a crucial role in designing efficient architectures for ML models including CNNs, SVMs, Decision Trees, and Gradient Boosting Machines. However, challenges related to hardware scalability, memory optimization, and accurate representation of complex ML operations remain open research areas. Continued innovation in VLSI design, combined with advancements in ML algorithms, will drive the development of high-performance diagnostic devices suitable for clinical and field applications. Ultimately, the integration of ML with VLSI opens new possibilities for point-of-care diagnostics, early tumor detection, and improved patient outcomes.

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