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DEPLOYMENT OF ENHANCED DEEP LEARNING MODEL WITH THE BEST ESTIMATORS ON OPTIMIZERS AND ACTIVATION FUNCTIONS FOR HEALTHCARE IN WEB APPLICATION

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ABSTRACT

Breast cancer and brain tumor stand as leading global causes of mortality. Brain tumor uses Magnetic Resonance Imaging (MRI) which offers superior clarity in visualizing brain structures compared to other imaging modalities, while Breast cancer uses ultrasonography (US) serves as a common tool for detecting breast cancer despite its inherent limitations in image quality. Motion artifacts frequently hinder MRI scans, necessitating skilled radiologists for accurate interpretation. Computer-aided diagnosis (CAD) systems driven by artificial intelligence, present a promising solution by consistently assisting radiologists in analyzing US images. Convolutional neural networks (CNNs) leverage various optimizers like Adam and Stochastic Gradient Descent (SGD), RMSprop, Adagrad, and Adadelta as well as activation functions including PReLu, LeakyReLu, Elu, and ReLu for their construction and training. The comparative analysis highlights the importance of optimizers and activation functions in deep learning algorithms for predicting brain tumors and breast cancer. The Adam optimizer combined with the ReLU activation function achieved an accuracy of 85% for breast cancer prediction, while RMSprop combined with ReLU activation function achieved a higher accuracy of 93% for brain tumor classification. From this research, considerable deep learning configurations are identified for both breast cancer and brain tumor prediction, facilitating more precise and efficient diagnoses. The comparative analysis provides valuable insights for those involved in medical imaging applications. Furthermore, The CNN model is deployed in web interface using flask framework to streamline the integration of these models into healthcare systems. This interface simplifies the input of medical data including image data and provides real-time predictions.

KEYWORDS—*Convolutional neural networks, Comparative Analysis, Activation functions, Optimizers, Ultrasound images, MRI images, Breast cancer, Brain tumor, medical imaging applications, FLASK.*

I. INTRODUCTION

Early detection and accurate diagnosis are critical for effective treatment and improved outcomes in breast cancer and brain tumors, two prevalent and potentially fatal conditions worldwide. Diagnosing cancer is often challenging due to the complex and varied characteristics of tumor appearance and growth [1]. Significant advancements in technology, particularly in the field of deep learning have revolutionized the development of predictive models in healthcare domain. By leveraging large datasets and complex neural network architectures, deep learning algorithms can effectively identify patterns and features in medical images, enhancing the precision and effectiveness of diagnoses for breast cancer and brain tumors. Over the last 26 years, there has been a notable increase in the age-standardized incidence rate of breast cancer among females, showing a rise of 39.1% (95% confidence interval, 5.1 to 85.5) [2].

Breast cancer and brain tumors are rare but lethal diseases affecting millions globally. While breast cancer targets breast tissue, brain tumors can develop within or around the brain. Despite their distinctions, both illnesses present significant challenges to patients, families, and healthcare providers. Each year, more than 250,000 individuals receive a diagnosis of brain tumors, with approximately 2% of cases identified as malignant [3]. This study aimed to assess the predictive potential of deep learning systems for breast cancer and brain tumors. Specifically, comparative analysis of optimizers and activation functions using a convolutional neural network (CNN) model focusing on these crucial elements of deep learning models.

Optimizers play a crucial role in training models by adjusting parameters such as weights and biases to enhance accuracy and convergence. These algorithms modify the model's parameters based on the evaluation provided by the loss function, aiming to minimize error. Popular optimizers include Adagrad, Stochastic Gradient Descent (SGD), Adam, RMSprop, and Adadelta.

TABLE I. DESCRIPTION OF OPTIMIZERS

OPTIMIZERS	FUNCTIONALITY
Adam (Adaptive Moment Estimation)	An optimization method that merges elements from both RMSprop and momentum, thereby creating an adaptive learning rate technique.
RMSprop (Root Mean Square Propagation)	RMSprop addresses the diminishing learning rate problem of AdaGrad by introducing adaptive adjustments to the learning rate.
AdaGrad (Adaptive	AdaGrad adapts the learning rate individually for each parameter by

Gradient Algorithm)	considering the historical gradients collected for that parameter.
Adadelta	Adadelta, an enhancement of RMSprop, reduces the need for a manually selected global learning rate.
Stochastic Gradient Descent (SGD)	It calculates the gradient using only one randomly chosen sample from the training dataset.

Activation functions introduce non-linearity to neural networks, allowing them to capture complex patterns within the data. These functions are applied to the output of each neuron layer before passing it to the next layer. Commonly used activation functions include PReLU, LeakyReLU, Elu, ReLU, Softmax, and Tanh.

TABLE II. DESCRIPTION OF ACTIVATION FUNCTIONS

ACTIVATION FUNCTIONS	FUNCTIONALITY
ReLU (Rectified Linear Unit)	It replaces all negative values in the input with zeros enhances sparsity and introduces non-linearity.
PRELU (Parametric Rectified Linear Unit)	In contrast to ReLU, PRELU allows for a slight training-derived slope to be present in the negative component of the input.
Leaky ReLU	A variation of the ReLU function designed to tackle the issue of dying ReLU by enabling a modest non-zero gradient for negative inputs.
ELU (Exponential Linear Unit)	A smooth negative value curve which minimizes problems arising from dead neurons.

Softmax and Tanh are used for binary classification as this research deals with multi-class classification these activation functions are not used.

This research aims to enhance the performance of deep learning models for predicting brain tumors and breast cancer by systematically evaluating different optimizers and activation functions within convolutional neural networks (CNNs). The objective is to pinpoint the optimal combination of optimizer and activation function that yields the highest prediction accuracy and resilience through thorough analysis of diverse configurations. The primary objective of this research is to support the development of more reliable and efficient diagnostic tools for these critical diseases. It is essential to bear in mind that while the overall process of analyzing data on brain tumors and breast cancer remains consistent. Exploring potential web interface designs for the streamlined CNN models using the Flask framework. Enhancing medical practitioners' access and utilization of deep learning models through internet applications accelerates diagnosis and treatment decision-making processes.

II. LITERATURE REVIEW

A. Breast Cancer

Swati Nadkarni et.al [4] Utilizing a combination of deep learning alongside diffusion weighted imaging (DWI) and dynamic contrast-enhanced MRI (DCE-MRI), this research aims to enhance the detection of breast cancer. It builds upon prior studies conducted by researchers which highlighted the complementary nature of DCE-MRI and DWI in lesion detection. Drawing from the methodologies for addressing class imbalances and improving dataset quality. The study addresses issues related to class imbalance and data augmentation. Employing convolutional neural network (CNN) architectures such as DenseNet-201, AlexNet, and Inception-V3, the research achieves a maximum accuracy of 90.8% with Inception-V3, showcasing the efficacy of deep learning in facilitating quicker detection of breast cancer lesions by radiologists. Amrisha R R et.al [5] study underscores the importance of timely diagnosis through precise analysis of medical imaging data, particularly in ultrasonography, mammography, and histopathology. Utilizing transfer learning and convolutional neural networks (CNNs), the study demonstrates how artificial intelligence (AI) in medical image analysis can enhance precision medicine and the diagnosis of breast cancer. This advancement aims to decrease the mortality rate associated with the disease by enabling early detection and tailored treatment strategies.

Mobarak Zourhri et.al [6] explores the application of deep learning techniques in the classification of breast cancer ultrasound images, specifically investigating the efficacy of transfer learning utilizing pre-trained models like VGG16, VGG19, MobileNetV2, and ResNet50V2. The evaluation was conducted using a dataset comprising 9016 ultrasound images. The findings suggest that transfer learning can enhance the accuracy of breast tumor identification from ultrasound images, offering potential advancements for computer-aided diagnosis systems. However, the study acknowledges its constraints and underscores the need for further research, particularly considering the dataset's size and the absence of patient-specific data. Nalinikanta Routray et.al [7] research delves into the application of deep learning methodologies, specifically RNN and GRU models, for detecting and treating breast cancer. It highlights the crucial role of preprocessing data to ensure accurate predictions, achieving an impressive accuracy rate of 97% with the GRU model. Deep learning outperformed standard classifiers in classification tasks, indicating its promising prospects for early cancer diagnosis. The study underscores the importance of timely breast cancer detection in enhancing patient prognosis.

The study of Md Harun or Rashid et.al [8] addresses the pressing need for timely detection of breast cancer, a condition that affects numerous women annually. It presents a novel CNN model and a Computer-Aided Diagnosis (CAD) system employing pre-trained Deep Learning algorithms (CNN, LSTM, and MLP). Emphasizing the critical role of early detection in mitigating the advancement of breast cancer, the research also proposes potential future applications, including an automated tool to assist physicians in early identification. Harsh Manishkumar et.al [9] proposes the utilization of an Adaptive Deep Convolutional Neural Network (ADCNN) for early breast cancer detection through mammography data analysis. The objective is to enhance computational effectiveness in diagnosing breast cancer by employing a flexible CNN framework, highlighting the importance of refined training methods to achieve the best results. Mokhairi Makhtar et.al [10] proposes an enhanced approach for predicting breast cancer by employing a multi-classifier based deep learning method. This method integrates classifiers such as SMO, J48, RFs, NB, and IBk, aiming to enhance prediction accuracy. It underscores the critical importance of early detection and efficient treatment in reducing breast cancer mortality rates. Moreover, the study delves into the utilization of deep learning in medical image processing, emphasizing its growing significance in the healthcare sector. Through the suggested Deep Multi-classifier Learning (DMCL) technique, which integrates feature selection and classification within a deep neural network architecture, a comprehensive approach is presented to enhance breast cancer detection. Rosepreet Kaur Bhogal et.al [11] The study underscores the crucial necessity for rapid technological advancements in combating this prevalent and life-threatening illness by offering a comprehensive examination of the utilization of deep learning and machine learning methodologies, with a particular focus on Convolutional Neural Networks (CNNs), in the timely detection and diagnosis of breast cancer.

B. Brain Tumor

Deep learning methods, particularly those utilizing MRI, have been increasingly employed in various imaging modalities for the prediction and classification of brain cancers Md. Shabir Khan Akash et.al [12].

Hanaa ZainEldin et.al [13] introduced an enhanced Brain Tumor Classification Model (BCM-CNN) employing Convolutional Neural Networks (CNNs) fine-tuned with an Adaptive Dynamic Sine-Cosine Fitness Grey Wolf Optimizer (ADSCFGWO). While the computational demands of this approach might delay real-time implementation, it also opens avenues for further exploration into scalability and predictive challenges beyond categorization. Taiwo Soewu et.al [13] underscores the significance of employing deep learning models, particularly Convolutional Neural Networks (CNNs), in medical imaging tasks to enhance the precision of tumor detection from MRI scans. These models leverage advancements in subsequent architectures like AlexNet.

Ayesha Younis et.al [14] utilizes the VGG 16 architecture to construct and train its model, resulting in outstanding accuracy in tumor detection. It examines various approaches and strategies from prior studies, underscoring the significance of automated categorization systems in enhancing detection efficacy. Almetwally M. Mostafa et.al [15] introduces a DL approach for brain tumor (BT) segmentation utilizing MRI data, underscoring DL's importance in medical image analysis. Employing a CNN structure, the model comprises stages for preprocessing, data organization, model training, and assessment. It underscores the promise of DL methods in enhancing the accuracy of BT diagnosis. Md. Saikat Islam Khan et.al [16] Research indicates that employing a 23-layer CNN architecture alongside a Fine-tuned CNN utilizing the VGG16 architecture proves effective across various dataset sizes, mitigating limitations associated with traditional methods. These findings underscore the efficacy of the proposed methodologies in improving brain tumor diagnosis and highlight their potential as superior alternatives in this domain. Shamim Ahmed et.al [17] Proposing an explanation-driven deep learning model, the research employs a convolutional neural network (CNN) leveraging EfficientNetB0 architecture alongside Shapley additive explanation (SHAP) to discern various brain tumor subtypes from MRI data. Notably, the solution integrates data augmentation techniques to address the challenge posed by unexpected imaging angles within the dataset, surpassing previous methodologies. This study underscores the significance of eXplainable Artificial Intelligence (XAI) in enhancing both quantitative assessment and visual proficiency, thereby showcasing the efficacy of the proposed approach in identifying and categorizing brain cancer. Poonam Shourie et.al [18] This article discusses the utilization of MRI images in diagnosing various types of brain cancer through the application of the deep convolutional neural network known as the VGG-16 model. By undertaking extensive data preparation and augmentation, the study harnesses the robust classification abilities of the VGG-16 architecture, showcasing potential advancements in the analysis of medical images for identifying brain tumors.

Ahmed s. musallam et.al [19] The research study introduces an innovative Deep Convolutional Neural Network (DCNN) structure along with a three-step preprocessing technique to precisely recognize brain disorders using MRI data. This approach demonstrates robustness in identifying pituitary anomalies, meningiomas, and gliomas in comparison to existing models.

III. METHODOLOGY

Brain tumors and breast cancer pose significant health challenges affecting millions globally, presenting complex issues for medical professionals and patients. The MRI scan produces numerous 2D image slices with excellent soft tissue contrast, all achieved without the need for ionizing radiation [20]. Brain tumors originate within or near the brain, whereas breast cancer primarily affects breast tissue. Breast cancer typically begins in breast tissue, where abnormal cell growth and mutation lead to the formation of tumors. Using CNN models, the classification of brain tumors and breast cancer prognosis is based on this approach. CNNs excel in extracting detailed features and categorizing them accurately from raw pixel data, making them well-suited for image-based tasks like medical imaging. It can enhance the performance of the CNN model for specific medical imaging purposes, such as classifying abnormalities indicative of breast cancer or brain tumors, by adjusting its parameters and architecture.

A. Dataset

The most prevalent form of cancer affecting women is breast cancer (BC). Globally, approximately 2.1 million women are at risk of succumbing to breast cancer, as per the World Health Organization (WHO) [21].

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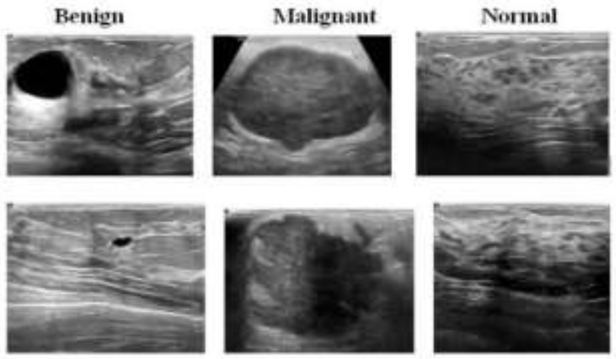

Fig. 1. Breast cancer ultrasound images of three classes.

As shown in "Fig.1" dataset containing ultrasound images of breast cancer (Dataset_BUSI_with_GT) is categorized into three groups: benign, malignant, and normal. A benign breast tumor is a growth that doesn't spread (metastasize) to other body organs. Typically, non-cancerous tumors pose minimal risk to life. Malignant tumors develop in or around breast tissue, typically within the milk ducts and glands. These tumors usually originate from abnormalities in cell growth, presenting as lumps or calcium deposits. Healthy breast cells are indicated as normal.

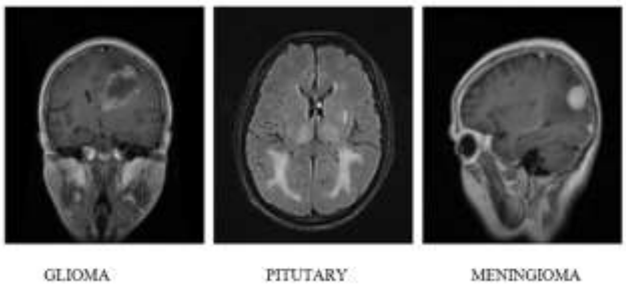

Fig. 2. Brain tumor MRI images of three classes.

Brain tumor is the most hazardous disease that develops in humans. The brain is a sophisticated organ of the human organ, which includes neurons and tissues that control most of the body's functions, including breathing, muscle movement, and our senses. Each cell grows with their capabilities, resist, and become abnormal. Brain tumors, also referred to as intracranial cancer, result from abnormal cell growth within the brain. As of 2021, the US has reported 24,530 cases, with 10,690 involving women and 13,840 involving men. Over the past three decades, the National Brain Tumor Foundation (NBTF) notes a 300% increase in death rates across various countries. Primary brain tumors are characterized by localized abnormal cell formation that doesn't spread to other parts of the body. As shown in "Fig.2." Brain tumor MRI Pictures Database (BT_MRI) collection contains 7023 human brain MRI pictures organized into three categories: glioma, meningioma, and pituitary. Gliomas, which originate from the supportive glial cells surrounding neurons in the brain, constitute approximately one-third of all brain cancer cases.

B. Model Planning

The main goal of the project is to develop Convolutional Neural Network (CNN) models for image classification, focusing on tasks such as detecting breast cancer and brain tumors. As depicted in "Figure 3," the initial phase involves importing the necessary libraries (scipy-learn, TensorFlow, Seaborn, PIL, Matplotlib, NumPy, and pandas) essential for data manipulation, visualization, and model development. Upon importing the dataset, preprocessing steps are applied, such as downsampling, grayscale conversion, reshaping, normalization, and augmentation. The CNN architecture comprises layers like Conv2D, MaxPooling2D, Flatten, and Dense with dropout regularization. The model is constructed trained on the training dataset, evaluated using validation data, and tested with a separate testing dataset to ensure its generalizability. This process involves selecting appropriate optimizers and loss functions. Finally, the trained model is deployed online using Flask, enabling users to utilize it for predicting new data.

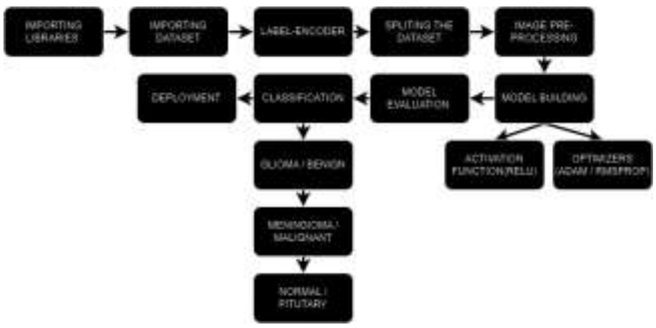

Fig.3. Model planning for both the datasets.

C. Data Preprocessing

The initial stages of constructing the preprocessing pipeline for the breast cancer ultrasound and brain tumor MRI images datasets involves five crucial steps. Firstly, data organization and label encoding were performed, where the datasets are structured into subfolders representing three different classes for each, and labels were encoded numerically using one-hot encoding. The dataset was then split into training and testing sets, ensuring balanced representation across classes. Following this, individual image preprocessing steps were applied, including loading, resizing, converting to grayscale, converting to NumPy arrays, reshaping, and normalization. Data augmentation was implemented exclusively on the training sets to create additional images with random transformations, enhancing model generalization. Finally, batching data for training was employed, presenting the model with batches of images to improve training efficiency. This involved using the ImageDataGenerator to iterate through training images in batches, optimizing resource utilization during training.

D. Convolutional Neural Network(CNNs)

CNNs have revolutionized computer vision applications by automating the recognition of objects within images for tasks like image categorization. Their ability to extract intricate features from raw image data has significantly advanced tasks such as item identification, scene interpretation, and visual data processing. Within the CNN architecture, convolutional layers employ convolving filters to extract features from input images, while input layers store the raw image data. On the other hand, pooling layers downsample images and reduce spatial dimensions. The output layer categorizes images into distinct groups based on learned features, while fully connected layers identify complex relationships between these features. CNNs

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are a subset of deep neural networks that have found widespread use in image recognition and classification, and their essential components are discussed here. CNNs are designed with interconnected layers of neurons, enabling them to autonomously learn from input data and extract relevant information. Convolutional layers, pooling layers, and fully linked layers are common components of this layer structure [22].

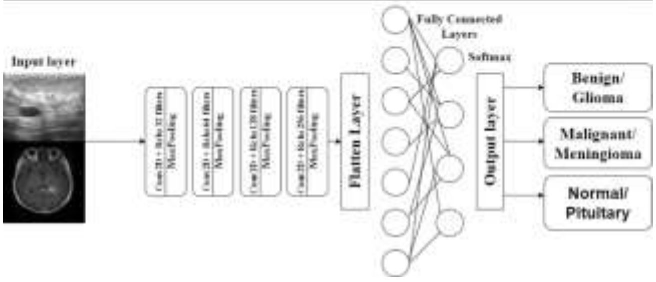

Fig.4.CNN Architecture for both breast cancer and brain tumor.

As shown in “Fig.4” within Convolutional Neural Networks (CNNs), convolutional layers are responsible for extracting fundamental visual components such as edges, textures, and shapes. Following this, pooling layers diminish spatial dimensions to preserve significant details. Subsequently, fully connected layers are employed to classify the extracted features, and the output layer produces probabilities for various classes. This hierarchical methodology empowers CNNs to effectively learn and recognize complex patterns in images, rendering them crucial for tasks like image classification and object recognition.

E. Comparitive Analysis

Comparative analysis plays a crucial role in the evaluation and advancement of deep learning algorithms for predicting diseases like breast cancer and brain tumors. By systematically comparing different optimizers and activation functions, significantly impacts a neural network's performance metrics such as accuracy, sensitivity, precision, and f1-score. This comparative analysis provides valuable insights into which combination of optimizer and activation function works best for the given datasets and problem domain. Activation functions like ReLU offer efficient training with its simplicity, while others like tanh can struggle with vanishing gradients. Optimizers like Adam are known for their adaptive learning rates, tackling issues faced by SGD (Stochastic Gradient Descent) but potentially converging slower. Selecting the best combination depends on the specific problem and dataset. Experimenting with different options is crucial to find the optimal configuration for neural networks.

IV. RESULTS

The system's performance is evaluated using the following performance metrics: True Negative (TN) signifies the correctly categorized benign samples, while True Positive (TP) denotes the accurately recognized malignant samples. False Positive (FP) indicates the mislabeling of benign samples as malignant, whereas False Negative (FN) represents the mislabeling of malignant samples as benign. These definitions characterize the subsequent measures.

A. Precision

Precision is the proportion of accurate positive forecasts among all forecasts that are positive as shown in Equation 1.

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

B. Recall

$$Recall(Sensitivity) = \frac{TP}{TP+FN} \qquad (2)$$

The total count, as defined by Equation 2, represents the cumulative number of malignant samples. A high sensitivity rating suggests that even with few false negatives, many disease-positive samples may still be accurately identified, minimizing the risk of missing them.

C. F1-Score

$$F1 - Score = \frac{2TP}{2TP+FP+FN} \qquad (3)$$

When class distribution is uneven, prioritizing the F1 score over accuracy becomes crucial, as it is a more meaningful metric. Equation 4 delineates the calculation of the F1 Score.

D. Accuracy

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

Equation 1 defines accuracy as the proportion of correctly identified samples out of the total number of samples.
The results showcase the effects of various combinations of optimizers and activation functions on two models.

TABLE III. COMPARING ADAM OPTIMIZER AND ACTIVATION FUNCTIONS WITH BOTH DATASETS.

Adam	Precision		Recall		F1- Score		Accuracy	
	BC	BT	BC	BT	BC	BT	BC	BT
Relu	0.87	0.92	0.85	0.92	0.86	0.92	0.88	0.92
LeakyRelu	0.81	0.91	0.86	0.90	0.83	0.91	0.83	0.90
PReLU	0.84	082	0.84	0.82	0.84	0.81	0.85	0.82
Elu	0.83	0.79	0.73	0.83	0.76	0.75	0.77	0.76

Table III illustrates that Relu exhibits outstanding recall, precision, and F1-score across datasets associated with brain tumors and breast cancer. Among all activation functions depicted, it achieves the highest accuracy. “Fig.5” shows the graphical representation of Comparison of Adam optimizer and activation functions.

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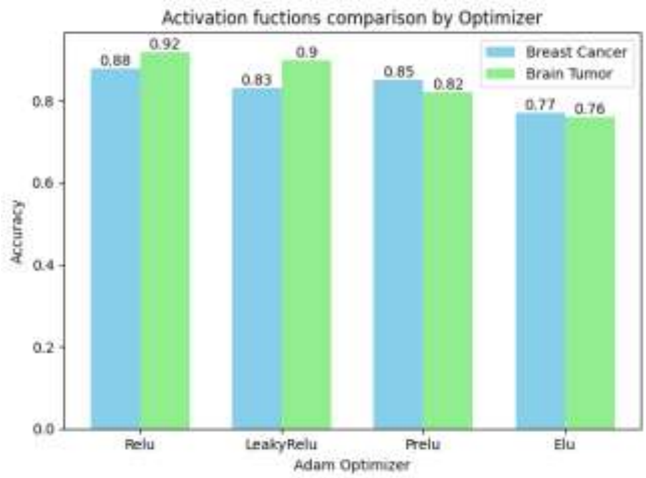

Fig.5. Comparison of Adam optimizer and activation functions.

TABLE IV. COMPARING SGD OPTIMIZER AND ACTIVATION FUNCTIONS WITH BOTH DATASETS.

SGD	Precision		Recall		F1- Score		Accuracy	
	BC	BT	BC	BT	BC	BT	BC	BT
Relu	0.76	0.74	0.55	0.71	0.59	0.70	0.67	0.71
LeakyRelu	0.77	0.75	0.60	0.75	0.59	0.74	0.67	0.75
PReLU	0.77	0.74	0.60	0.69	0.59	0.73	0.70	0.68
Elu	0.74	0.77	0.54	0.72	0.56	0.73	0.66	0.69

As described in Table IV, Relu demonstrates a moderate level of accuracy, precision, recall, and F1-score. While yielding acceptable results, it falls short compared to other optimizers. An illustration of the contrast between activation functions and SGD optimizer is shown in "Fig.6".

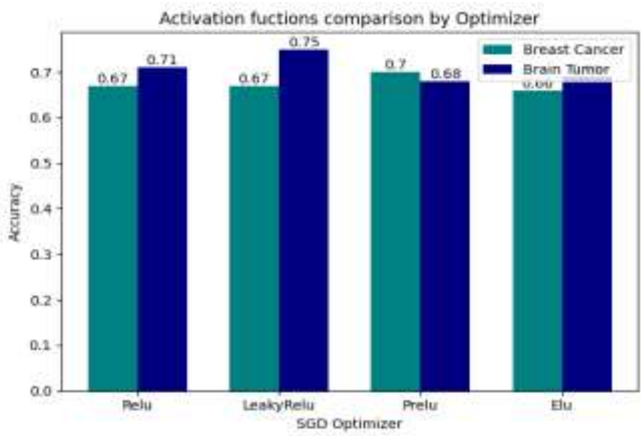

Fig.6. Comparison of SGD optimizer and activation functions.

TABLE V. COMPARING RMSPROP OPTIMIZER AND ACTIVATION FUNCTIONS WITH BOTH DATASETS.

Rmsprop	Precision		Recall		F1- Score		Accuracy	
	BC	BT	BC	BT	BC	BT	BC	BT
Relu	0.85	0.93	0.81	0.93	0.82	0.93	0.84	0.93
LeakyRelu	0.81	0.94	0.81	0.93	0.80	0.94	0.82	0.93
PReLU	0.83	0.91	0.83	0.88	0.83	0.90	0.84	0.90
Elu	0.84	0.88	0.76	0.92	0.79	0.89	0.81	0.92

In table V, Relu demonstrates consistent performance with commendable F1-score, accuracy, precision, and recall across both datasets. Its notable recall across both datasets distinguishes it from other activation functions, consistently surpassing them. "Fig. 7" illustrates a visual comparison between the RMSprop optimizer and different activation functions.

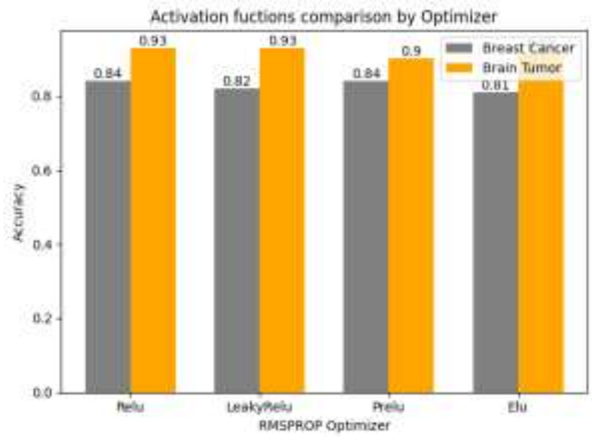

Fig.7. Comparison of RMSprop optimizer and activation functions.

TABLE VI. COMPARING ADAGRAD OPTIMIZER AND ACTIVATION FUNCTIONS WITH BOTH DATASETS.

Adagrad	Precision		Recall		F1- Score		Accuracy	
	BC	BT	BC	BT	BC	BT	BC	BT
Relu	0.36	0.68	0.33	0.55	0.25	0.52	0.56	0.56
LeakyRelu	0.37	0.69	0.33	0.66	0.25	0.63	0.56	0.66
PReLU	0.19	0.69	0.33	0.66	0.24	0.63	0.56	0.66
Elu	0.74	0.71	0.52	0.68	0.53	0.67	0.65	0.68

Table VI, ReLU demonstrates moderate performance across both datasets. "Fig.8" shows the graphical representation of Comparison of Adagrad optimizer and activation functions.

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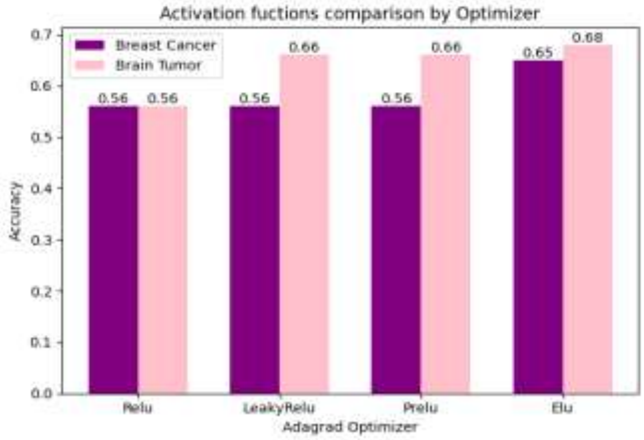

Fig.8. Comparison of Adagrad optimizer and activation functions.

TABLE VII. COMPARING ADADELTA OPTIMIZER AND ACTIVATION FUNCTIONS WITH BOTH DATASETS.

Adadelta	Precision		Recall		F1- Score		Accuracy	
	BC	BT	BC	BT	BC	BT	BC	BT
Relu	0.19	0.23	0.33	0.34	0.24	0.21	0.56	0.37
LeakyRelu	0.19	0.35	0.33	0.35	0.24	0.20	0.56	0.37
PReLU	0.36	0.34	0.33	0.35	0.25	0.21	0.56	0,41
Elu	0.19	0.31	0.33	0.35	0.24	0.21	0.56	0.37

Table VII illustrates that the utilization of Relu activation in combination with Adadelta optimization yields lower accuracy, recall, and F1-score metrics for both datasets. Despite the suboptimal overall performance, brain tumors are identified more accurately compared to breast cancer. A depiction showcasing the differentiation between activation functions and the Adadelta optimizer is available in "Figure 9".

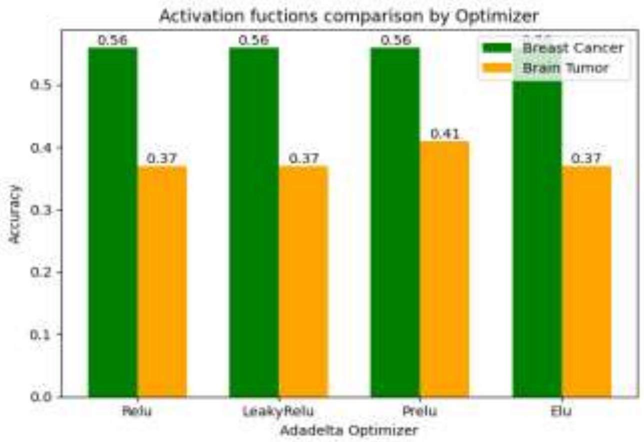

Fig.9. Comparison of Adadelta optimizer and activation functions.

In summary, these findings indicate that the combinations of optimizer and activation function are effective. For instance, using the Adam optimizer and ReLU activation function led to an 85% accuracy in the breast cancer classification model. Similarly, the brain tumor classification model achieved a high accuracy of 93% by using the ReLU activation function and RMSprop optimizer.

REFERENCES

1. *Y. Guo, Y. Gao and D. Shen, "Deformable MR Prostate Segmentation via Deep Feature Learning and Sparse Patch Matching, 2016.*
2. *India State-Level Disease Burden Initiative Cancer Collaborators. The burden of cancers and their variations across the states of India: The Global Burden of Disease Study 1990-2016. Lancet Oncol. 2018; 19:1289–1306.*
3. *Tiwari, P.; Pant, B.; Elarabawy, M.M.; Abd-Elnaby, M.; Mohd, N.; Dhiman, G.; Sharma, S. CNN Based Multiclass Brain Tumor Detection Using Medical Imaging. Compute. Intell. Neurosci. 2022.*
4. *Swati Nadkarni, Kevin Noronha" Breast Cancer Detection with Multiparametric Magnetic Resonance Imaging using Deep Learning". 2023.*
5. *Amrisha R R, Monika M, Yamuna V, Arun Kumar S, Sasikala S" Enhanced Breast Cancer Detection in Multiple Imaging Modalities using Deep Learning",2023.*
6. *Mobarak Zourhri, Soufiane Hamida, Nouhaila Akouz, Bouchaib Cherradi, Hasna Nhaila, Mohamed El Khaili," Deep Learning Technique for Classification of Breast Cancer using Ultrasound Images",2023.*
7. *Nalinikanta Routray, Saroja Kumar Rout, Bandita Sahu," Breast Cancer Prediction Using Deep Learning Technique RNN and GRU",2022.*
8. *Md Harun or Rashid, S.M Shahriyar, F M Javed Mehedi Shamrat, Tanzil Mahbub, Zarrin Tasnim, Md Zunayed Ahmed," A Convolutional Neural Network based Classification Approach for Breast Cancer Detection",2023.*
9. *Shah Harsh Manishkumar, P Saranya ," Detection and Classification of Breast Cancer from Mammogram Images Using Adaptive Deep Learning Technique",2022.*
10. *Mokhairi Makhtar, Rosaida Rosly, Mohd Khalid Awang, Mumtazimah Mohamad, Aznida Hayati Zakaria," A Multi-Classifier Method based Deep Learning Approach for Breast Cancer",2020.*
11. *Rosepreet Kaur Bhogal , Pyda Dhruva Suchit , Chellagundla Naresh "Review: Breast Cancer Detection Using Deep Learning",2021.*
12. *Md. Shabir Khan Akash , Md. Al Mamun "A Comparative Analysis on Predicting Brain Tumor from MRI FLAIR Images using Deep Learning",2023*
13. *Hanaa ZainEldin, Samah A. Gamel, El-Sayed M. El-Kenawy, Amal H. Alharbi , Doaa Sami Khafaga , Abdelhameed Ibrahim ,andFatmaM.Talaat, "Brain Tumor Detection and Classification Using Deep Learning and Sine-Cosine Fitness Grey Wolf Optimization", Dec 2022.*
14. *Taiwo Soewu, Dalwinder Singh, Manik Rakhra, Gouri Shankar Chakraborty, Arun Singh," Convolutional Neural Networks for MRI-Based Brain Tumor Classification",2022.*
15. *Ayesha Younis , Li Qiang , Charles Okanda Nyatega and Halima Bello Kawuwa," Brain Tumor Analysis Using Deep Learning and VGG-16 Ensembling Learning Approaches",July 2022.*
16. *Almetwally M. Mostafa 1 , MohammedZakariah 2 and EmanAbdullah Aldakheel ," Brain Tumor Segmentation Using Deep Learning on MRIImages", April 2023.*
17. *Md. Saikat Islam Khana, Anichur Rahmana,b,, Tanoy Debnatha,c, Md. Razaul Karima, Mostofa Kamal Nasira, Shahab S. Bandd, Amir Mosavie,f, Iman Dehzangi," Accurate brain tumor detection using deep convolutional neural network", Aug 2022.*
18. *Shamim Ahmed, Sm Nuruzzaman Nobel, and Oli Ullah," An Effective Deep CNN Model for Multiclass Brain Tumor Detection Using MRI Images and SHAP Explainability",2023.*
19. *Poonam Shourie, Vatsala Anand, Sheifali Gupta" An Intelligent VGG-16 Framework for Brain Tumor Detection Using MRI-Scans",2023.*

20. *AHMED S. MUSALLAM, AHMED S. SHERIF , AND MOHAMED K. HUSSEIN "A New Convolutional Neural Network Architecture for Automatic Detection of Brain Tumors in Magnetic Resonance Imaging Images",2022*
21. *I¸sın, A.; Direko˘glu, C.; ¸Sah, M. Review of MRI-based brain tumor image segmentation using deep learning methods. Procedia Comput. Sci.*
22. *Pravin Kumar Samanta, Nirmal Kumar Rout, Ganapati Panda, "A novel deep CNN model for improved breast cancer detection using ultrasound images",2023.*
23. *Selvakumar Thirumalaisamy , Kamaleshwar Thangavilou Nazik Alturki , Sandeep kumar Mathivanan , Hariharan Rajadurai , Oumaima Saidani , Prabhu Jayagopal andSaikatGochhait ," Breast Cancer Classification Using Synthesized Deep Learning Model with Metaheuristic Optimization Algorithm", Sept 2023.*