Brain Tumor Detection In MRI Scans Using Hybrid AI Techniques

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Abstract – Better patient outcomes result from early diagnosis and treatment planning, which depends on the identification of brain tumors. By fusing deep learning, machine learning, and feature extraction approaches, this study explores the application of hybrid AI techniques for automated tumor diagnosis in MRI scans. The suggested method improves accuracy, robustness, and efficiency by combining conventional machine learning classifiers with convolutional neural networks (CNNs) for feature extraction. The results of the experiment demonstrate how well hybrid AI models distinguish between areas impacted by tumors and healthy tissues, which makes them an important tool for computer-aided diagnosis in medical imaging. In particular, this technique improves classification accuracy by combining Convolutional Neural Networks (CNNs) with Support Vector Machines (SVMs), and incorporates Generative Adversarial Networks (GANs) with Transfer Learning to refine feature representation in limited datasets. Experimental results indicate that these hybrid AI models achieve an average accuracy of 96.18%, demonstrating their potential for early brain cancer detection. The system enhances image quality, applies edge detection, extracts critical features, and leverages a hybrid AI-based training model, significantly improving diagnostic precision and surpassing previous methods.

Keywords— Convolutional Neural Networks (CNNs), Magnetic Resonance Image (MRI), Brain Tumor Detection, Support Vector Machines (SVMs), Generative Adversarial Networks (GANs).

I. INTRODUCTION

One of the most dangerous medical disorders, brain tumors requires prompt identification and precise diagnosis in order to be effectively treated. Because of its high-resolution soft tissue contrast, which makes it possible to precisely visualize brain abnormalities, magnetic resonance imaging (MRI) is a commonly utilized neuroimaging technology. However, manually identifying brain tumors from MRI scans is a laborious and subjective procedure that frequently results in different radiologists' interpretations. In order to overcome these obstacles, methods based on artificial intelligence (AI) have become useful instruments for automating the identification of brain tumors, increasing precision and effectiveness. Recent advancements in AI, particularly deep learning and

machine learning, have significantly transformed medical image analysis. However, relying on a single AI model may not always yield optimal results due to variations in tumor size, shape, and intensity across different MRI scans. As a result, hybrid AI techniques, which integrate multiple models and algorithms, have gained prominence for enhancing tumor classification, segmentation, and detection.

This study introduces a hybrid artificial intelligence (AI) method for MRI brain tumor detection that combines Generative Adversarial Networks (GANs) and Transfer Learning to improve feature representation, with Convolutional Neural Networks (CNNs) and Support Vector Machines (SVMs) to increase classification accuracy. CNNs effectively extract spatial characteristics from medical pictures, and SVMs are dependable classifiers that can differentiate between areas that are tumorous and those that are not. GANs contribute to data augmentation, addressing the challenge of restricted MRI datasets, and transfer learning improves performance on fresh datasets by utilizing pre-trained models. Brain tumors are abnormal cell growths in the brain that can be either benign or malignant. MRI remains the preferred imaging technique for diagnosing these tumors due to its superior resolution and contrast. While traditional machine learning techniques have played a crucial role in tumor detection and classification, recent deep learning models have demonstrated greater accuracy in feature extraction and classification, making them a promising approach for improving diagnostic precision.

The nervous system, which is made up of billions of neurons, synapses, and nerve cells, controls many vital bodily functions. Like any other organ, the brain is vulnerable to various conditions, including tumors. These tumors result from abnormal cell growth in specific brain regions, significantly affecting a patient's neurological health and overall.

The intricacy of the brain's structure makes diagnosing and treating brain cancers particularly difficult. Gliomas, meningiomas, and pituitary tumors are just a few of the different ways these tumors can appear; in other circumstances, there may not be any tumor at all. With over 120 distinct tumor types, each varying in size and characteristics, accurately identifying and classifying them is particularly difficult. Effective treatment planning depends on precise tumor segmentation, which involves identifying necrotic centers, edema, and tumorous tissues. Given these challenges, automated medical image recognition and classification play a crucial role in brain tumor diagnosis. Advanced computational techniques can enhance accuracy and efficiency, aiding in early detection and improving patient outcomes [1].

For better patient outcomes and treatment efficacy, brain tumors must be identified and classified early. However, it takes a lot of time and effort for medical practitioners to effectively classify brain cancers from big medical imaging datasets. With magnetic resonance imaging (MRI) being the gold standard for analyzing brain anatomy, neuroimaging methods like computed tomography (CT), positron emission tomography (PET), and MRI are essential for identifying brain cancers [2]. Because of its extensive use and efficiency in examining brain regions, MRI is the subject of this study. MRI offers high-resolution imaging for locating ROIs, but it might be challenging to reliably differentiate tumors due to machine-induced changes in intensity levels. Multimodal MRI scans, which include T1-weighted, T5-weighted, T2-weighted, and Fluid Attenuation Inversion Recovery (FLAIR) images, provide supplementary features to improve information extraction and help differentiate between distinct glioma sub-regions. Automatically segmenting brain tumors in multimodal MRI images is still a difficult task in medical image processing, even with the advances in medical imaging technology. Enhancing the precision and effectiveness of tumor identification and classification requires ongoing research and the creation of cutting-edge AI-driven methods [3].

Brain tumors, which arise from In medicine, aberrant cell growth in the brain or adjacent tissues poses a serious problem. These tumors vary widely in cellular composition, morphology, and location. Among primary brain tumors, gliomas are the most common and are further classified into astrocytomas, oligodendrogliomas, and glioblastomas. Meningiomas, which originate in the meninges and typically grow slowly, add another layer of complexity. Additionally, brain metastases—tumors that spread from other parts of the body—can result in diverse symptoms depending on their location and progression. Given this complexity, the development of reliable detection methods is crucial for accurate diagnosis and treatment planning. Magnetic Resonance Imaging (MRI) is a powerful diagnostic tool that enables the visualization of brain structures and abnormalities, helping detect potential signs of cancer. Different types of brain tumors exhibit distinct behaviors and prognoses, making precise classification essential for effective treatment strategies. As a key tool in neuroimaging, MRI provides high-resolution anatomical images and differentiates various tissue types, making it invaluable for medical professionals [4].

However, MRI-based tumor identification faces a number of difficulties. Variability in image quality can be introduced by elements including hardware-related distortions, magnetic field homogeneities, and patient movement. These discrepancies could make it harder to see small features, which would make tumor delineation less accurate. Because of the complexity of brain anatomy and the variety of tumor types, sophisticated imaging methods that can identify minute alterations in tissue composition are required to improve diagnostic accuracy. This follow is the structure of the article. Section II details previous efforts at brain tumor detection, and Section III details the full procedure that has been suggested. The findings from the performance evaluation of the proposed approach are reported in Section IV. Section V delves into the research's conclusions.

II. SURVEY OF LITERATURE

Numerous artificial intelligence (AI) strategies have been used in the extensive study on automated brain tumor identification in MRI scans. The accuracy of tumor segmentation and classification has been improved through the use of both Machines learning (ML) and deep learning (DL) techniques. However, individual models often face challenges such as limited dataset availability, complex tumor morphology, and variations in MRI quality. This section examines significant advancements in AI-driven brain tumor detection, emphasizing the strengths and limitations of different approaches. By exploring various techniques, researchers aim to develop more robust and efficient models capable of improving diagnostic accuracy and aiding in early detection.

Hossain et al. (2020) proposed a CNN-based model for brain tumor segmentation, achieving high accuracy without the need for manual feature extraction. Likewise, Khan et al. (2021) introduced a U-Net-based segmentation approach, which significantly improved tumor boundary delineation in MRI scans. Despite their effectiveness, CNN models often rely on large annotated datasets, posing a challenge in medical imaging due to data scarcity. To overcome the limitations of standalone AI models, researchers have explored hybrid AI techniques that integrate multiple models. These hybrid approaches aim to enhance segmentation accuracy, improve robustness, and address data constraints by leveraging the strengths of different AI methodologies [6].

In order to classify brain tumors, Chaudhary et al. (2022) developed a hybrid CNN-SVM model that uses Support Vector Machines (SVMs) for effective classification and Convolutional Neural Networks (CNNs) for feature extraction. Their method

demonstrated the efficacy of combining several strategies by outperforming independent CNN models in terms of accuracy. The application of Generative Adversarial Networks (GANs) for data augmentation is another exciting development that helps address the problem of sparse labeled MRI datasets. GANs improve model training by producing artificial but realistic medical images, which increases the generalizability and resilience of AI-based tumor detection systems [7].

Sharma et al. (2023) employed Generative Adversarial Networks (GANs) to generate synthetic MRI scans, improving the training process for deep learning models by addressing data scarcity. Additionally, Transfer Learning (TL) has been leveraged to enhance model performance by utilizing pre-trained networks such as ResNet and VGG-16, as demonstrated in Patel et al. (2023). Bhandari et al. (2022) explored the effectiveness of ResNet and Efficient Net architectures, reporting improved accuracy in multiclass tumor classification. These hybrid strategies have proven effective in refining tumor classification while mitigating the challenges associated with limited labeled data. Recent developments in MRI-based brain tumor classification have greatly increased the accuracy of detection. A technique for recognizing and locating several kinds of brain tumors in MRI images was presented in the study in [8] [9].

In [10], researchers developed tools for detecting gliomas, meningiomas, and pituitary tumors. This model leveraged a Convolutional Neural Network (CNN) to extract and analyze hidden information from MRI images. When compared to Multi-layer Perceptron (MLP), Stacking, XGBoost, Support Vector Machine (SVM), and Radial Basis Function (RBF) kernel methods, the proposed approach achieved an impressive accuracy result is 93.68%. The study focused on utilizing Deep Learning (DL) algorithms and MRI image processing to distinguish between different brain tumor types. Among all tested models, VGG16 demonstrated the highest classification accuracy.

Various algorithms have been employed for brain tumor detection and classification, including Multi-Layer Perceptron (MLP), K-Nearest Neighbors (KNN), Random Forest (RF), Naïve Bayes (NB), and Support Vector Machine (SVM) are a few examples. The classification accuracy of conventional SVM models was 92.5%. Additionally, researchers developed a five-layer Convolutional Neural Network (CNN) architecture, which demonstrated an impressive 97.7% accuracy in detecting brain tumors from MRI scans. In [11], two primary identification methods were trained using CNN on transverse brain tumor images, achieving a maximum accuracy of 91.42%. CapsNet, introduced in [12], was designed to enhance brain tumor analysis by encapsulating MRI images with a coarse tumor boundary. This approach resulted in an accuracy of 90.81%, highlighting its potential in brain tumor detection and segmentation.

To enhance data representation learning, we present a framework for hybrid AI techniques that effectively captures complex data correlations. To increase classification accuracy, this method combines Convolutional Neural Networks (CNNs) and Support Vector Machines (SVMs), while Generative Adversarial Networks (GANs) and Transfer Learning enhances feature representation, particularly in cases with limited datasets. Hybrid AI techniques serve as a comprehensive framework capable of handling intricate data relationships and multimodal inputs. Within this framework, traditional CNNs play a crucial role in feature extraction. To evaluate its effectiveness, experiments were conducted on visual object recognition and citation network classification tasks. Comparative analyses on four datasets against conventional models and CNN-based methods demonstrated that hybrid AI techniques consistently outperformed existing approaches. These findings suggest that the suggested hybrid AI framework is a promising option for cutting-edge AI-driven applications since it outperforms state-of-the-art techniques in learning intricate and highly linked data representations.

III. PROPOSED SYSTEM

Brain tumor investigation, diagnosis, and therapy planning is greatly assisted by MRI. The doctor can use it to learn about the history of brain tumors. Due to the brain's intricate anatomy, detecting brain tumors with MRI scans is no easy feat. An abnormal development of brain cells is known as a brain tumor. A variety of human soft tissues can be better contrasted in MRI scans. Three datasets make up this dataset: fig share, SARTAJ dataset, Br35H[15]. There are 7023 MRI scans of the human brain in this collection, and they fall into one of four categories: meningioma, glioma, no tumor, or pituitary.

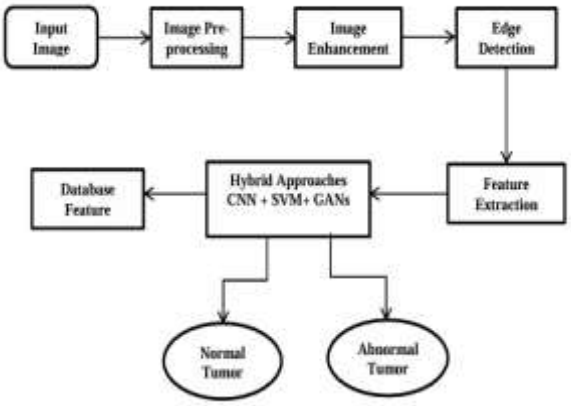


Fig. 1. **Propsoed Block Diagram for Brain Tumor Detection**

The following is a list of all the resources, datasets, and procedures that went into developing the algorithm for brain MR image tissue segmentation. Figure 1 is a flow of the whole method that incorporates testing and training.

A. Image Enhancement:

The process of enhancing a digital image without being aware of the original source's deterioration is known as image augmentation. Enhancement techniques are broadly categorized into direct and indirect approaches. The direct method focuses on visual contrast by displaying the image before applying contrast improvements, whereas the indirect method does not rely on visual contrast adjustments [13]. A key limitation of contrast enhancement techniques is the risk of over-enhancing certain regions while leaving others under-enhanced. Common image enhancement operations include adjusting brightness and contrast, reducing background noise, sharpening edges, and applying filtering techniques. These enhancements significantly improve the quality of MRI scans, leading to a more precise visualization of brain structures. Additionally, filtering and artifact removal techniques further refine the images, ensuring clearer and more accurate medical analysis.

1. Median Filter:

The median filter is an effective technique for reducing salt-and-pepper noise in Magnetic Resonance Imaging (MRI) scans. It works by eliminating high-frequency noise while preserving the edges of the image, ensuring that important structural details remain intact. By calculating the median of the nearby pixel values within a specified neighborhood, this filtering technique finds the new de-noised pixel value. The procedure entails choosing the middle value as the new pixel intensity after sorting the pixel values in ascending order. This approach helps in maintaining image sharpness while effectively suppressing noise. Where i (f, h) represent the filtered image output, and t (f, h) denotes the original image pixel values. This method enhances the overall quality of MRI scans, aiding in more accurate medical analysis and diagnosis.

$$\hat{i}(q, w) = \underset{(f,h)\in C}{\text{median}}\{t, (f, h)\} \quad (1)$$

b. Edge Detection:

Edge detection is a technique used to identify and locate distinct boundaries within an image by detecting abrupt changes in pixel intensity. These intensity discontinuities define the edges of objects in a scene [14]. Traditional edge detection methods guide the operator to disregard uniform regions while emphasizing areas with significant gradient changes. The operator is then applied to the image to highlight these edges. Various edge detection operators exist, each optimized for handling specific types of edges, such as step edges or gradual transitions. In a broader sense, edge detection plays a crucial role in reducing image data while retaining essential structural details. This simplification is an essential step in medical image analysis, particularly MRI-based brain tumor diagnosis, since it makes it easier to do further image processing tasks like object recognition, segmentation, and feature extraction.

c. Feature Extraction:

A feature vector is a condensed representation of a large and redundant dataset, enabling an algorithm to process data more efficiently. Feature extraction involves identifying and retrieving key characteristics essential for image classification. In the case of brain MRI analysis, texture features can be extracted from segmented images to reveal important structural properties. The Gray Level Co-occurrence Matrix is one of the most popular and successful techniques for extracting texture features (GLCM). GLCM analyzes the spatial relationships between pixel intensities in an image, capturing textural patterns that distinguish different regions. By reducing the number of gray levels, the GLCM approach minimizes computational complexity while maintaining high classification accuracy, making it a competitive technique for medical image analysis [15]. GLCM features are particularly useful for distinguishing between healthy brain tissue and abnormalities.
It provides a global measure of the intensity contrast between adjacent pixels in an image.

$$\text{con} = \sum_{c=0}^{C_{t-1}} c^2 \sum_{f=0}^{C_{t-1}} \sum_{h=0}^{C_{t-1}} d(f, h)^2 \quad (2)$$

i. Homogeneity:

It provides an indicator of how near the GLCM diagonal the distribution of GLCM elements happens to be.

$$\text{Hom} = \sum_{f=0}^{C_{t-1}} \sum_{h=0}^{C_{t-1}} \frac{d(f, h)}{\left(1 + \text{mod}(f, h)\right)} \quad (3)$$

ii. Energy:

The number of pixel-pair repeats, or textural homogeneity, can be measured with this metric.

$$E = \sum_{f=0}^{C_{t-1}} \sum_{h=0}^{C_{t-1}} d(f, h)^2 \quad (4)$$

Collecting MRI brain pictures, applying preprocessing processes and segmentation are the steps necessary to classify the brain as normal or pathological. Using the segmented image, GLCM is employed to extract texture features.

d. Hybrid Model Training:

The learning statement for CNN:

One kind of deep learning model made especially for handling organized, grid-like input, like pictures, is called a convolutional neural network (CNN). CNNs are very good at segmenting, classifying images, and detecting objects because they use convolutional

layers to extract spatial data. Convolution is the fundamental function of CNNs and is represented as:

$$Z(i,j)=\sum m\sum nX(i-m,j-n)\cdot K(m,n)Z(i,j) \quad (5)$$

After convolution, an activation function (commonly ReLU) is applied:

$$f(x)=\max(0,x)\ f(x) \quad (6)$$

Max Pooling:

$$P(i,j)=\max m,nX(i+m,j+n)P(i,j) \quad (7)$$

The learning statement for SVM:

Encouragement A supervised learning algorithm for classification, regression, and outlier detection is called a support vector machine (SVM). Finding the ideal hyperplane to divide data points from various classes is how it operates. SVM is a strong machine learning method that performs exceptionally well in applications involving regression and classification. It can effectively handle both linear and non-linear problems by utilizing kernel methods and margin maximization. The decision hyperplane in an N-dimensional space for an input feature vector xxx is provided by:

$$wTx+b=0 \quad (8)$$

The learning statement for GANs:

In 2014, Ian Good fellow presented a class of deep learning models called Generative Adversarial Networks (GANs). They are made up of two rival neural networks—a discriminator and a generator—that are simultaneously trained using a game-theoretic framework. Among the most intriguing advancements in deep learning are GANs, which make it possible to generate realistic data for a range of applications. However, to produce excellent results, they need to be carefully trained and adjusted.

GANs optimize the min-max objective function:

$$\text{Min(G) Max(D) } V(D,G)=Ex\sim Pdata(x)[\log D(x)]+Ez\sim Pz(z)[\log(1-D(G(z)))] \quad (9)$$

Analysis of Hybrid Model:

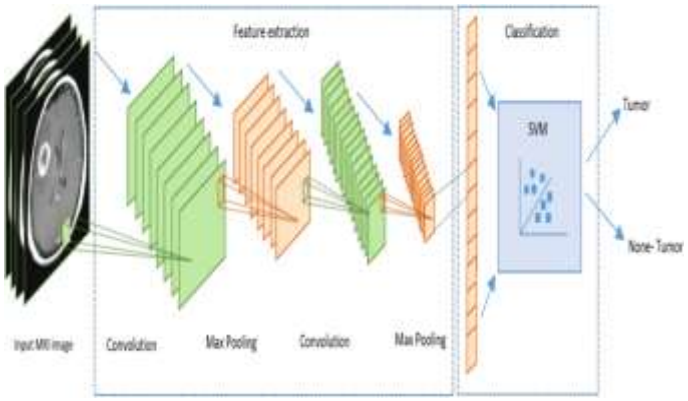


Fig. 2. ***Framework for Proposed Hybrid Mode***

Figure 2 shows a framework for classifying brain tumors from MRI images that combines machine learning and deep learning methods. First, a Convolutional Neural Network is used to extract features, where convolutional layers identify important spatial features,

and max pooling layers reduce dimensionality while preserving essential information. This hierarchical feature extraction is performed through multiple layers to capture complex patterns within the MRI images. After that, a Support Vector Machine (SVM) classifier receives the extracted characteristics and classifies the MRI scan as either "Tumor" or "Non-Tumor." This method improves the precision and effectiveness of brain tumor detection by fusing SVM for classification with CNNs for automated feature extraction.

IV. RESULT & DISCUSSION

Most cells in the human body undergo mitosi, a natural process of cell division that ensures growth, repair, and maintenance. However, when cells lose their ability to regulate growth, uncontrolled proliferation occurs, leading to the formation of tumors. Brain tumors develop when brain cells multiply abnormally and uncontrollably, disrupting normal neurological function. These tumors can be benign (non-cancerous) or malignant (cancerous), with varying degrees of aggressiveness. Their growth can exert pressure on surrounding brain structures, affecting cognitive and motor functions, making early detection and accurate classification essential for effective treatment.

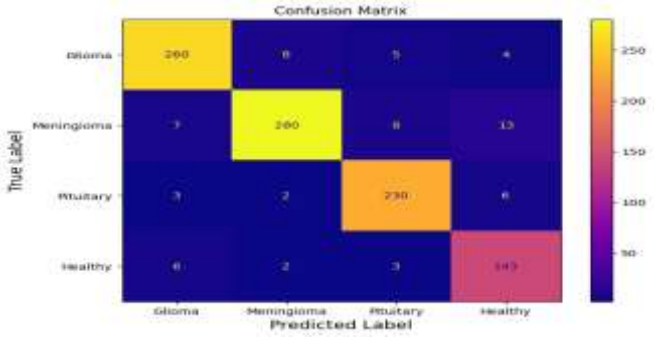


Fig. 3. ***Confusion Matrix Analysis for Proposed Model***

Each row in the matrix represents the actual value of instances, whereas each column represents the projected value. Eliminating or significantly lowering the rate of false positive and negative findings in medical research models is crucial. Both the positive and negative false positive rates are illustrated in Figure 3.

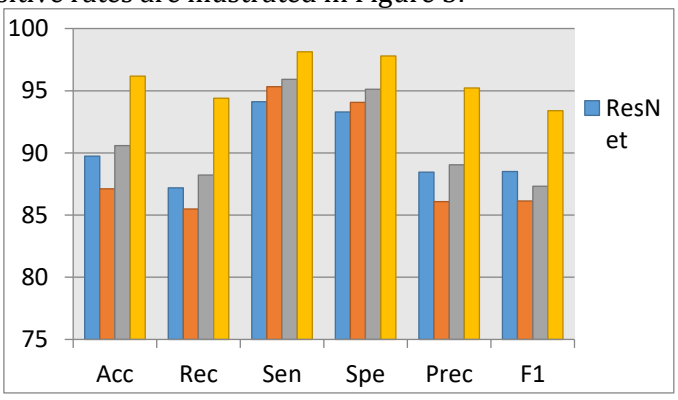


Fig. 4. **Hybrid Model Comparison Metrics**

Fig. 4 displays the model's performance comparison. With the f1 score, recall, and precision all in hand, we can see that hybrid model beats out all the other supporting techniques when it comes to detecting brain tumors.

The ROC curves of the suggested models for brain tumor classification are shown in Figure 5.

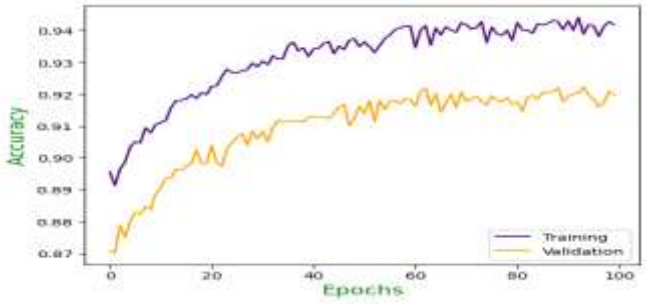


Fig. 5. ***Training and Validation Accuracy of Hybrid Model***

Figure 5 displays the outcomes of running the Hybrid model on both the training and validation datasets. Using the training data to train the Hybrid model for 100 epochs yielded a validation accuracy of 94.35% and a training accuracy of 96.17%.

TABLE I. ***EVALUATION PERFORMANCE (%)***

Models	Acc	Rec	Sen	Spe	Prec	F1
ResNet	89.74	87.20	94.12	93.30	88.44	88.50
HGAT	87.12	85.50	95.33	94.06	86.09	86.13
GCN	90.58	88.21	95.91	95.12	89.03	87.31
Hybrid Model	96.17	94.39	98.12	97.80	95.22	93.40

Table I compares the results of Spectral Graph Theory, CNN, and SVM, three distinct categorization models. The four main measures of model performance Accuracy (Acc), Sensitivity (Sp), Specificity (Sp), and Precision are listed in the table.

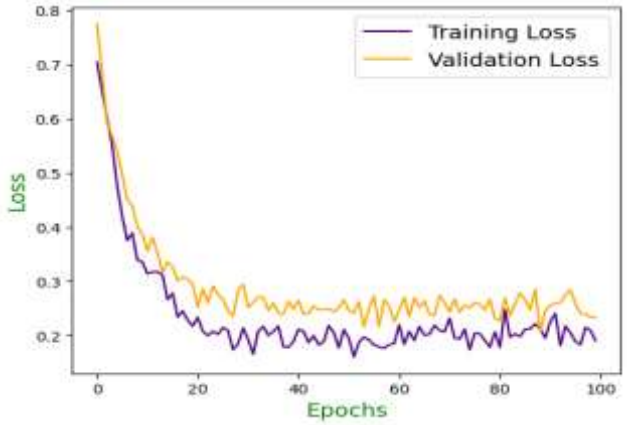


Fig. 6. ***Training and Validation Loss of Hybrid Model***

Loss as a function of training and validation datasets using the Hybrid model is shown in Figure 6. After 100 iterations of using the Hybrid model with the training data, the training loss is 0.25 percent and the validation loss is 0.20 percent.

V. CONCLUSION

Medical professionals execute the crucial yet labor-intensive manual process of tumor segmentation from MRI data. Because tumor tissues can seem very different from patient to patient and in many situations very similar to normal tissues, automating this procedure is no easy feat. MRI is a cutting-edge medical imaging method that reveals a wealth of data regarding the structure of human soft tissues. It is possible to identify and separate a brain tumor from MRI scans using a variety of techniques. Image enhancement is the process of improving digital photos in a way that does not reveal any degradation of the original source image. Detecting crisp visual discontinuities is what edge detection is all about. Feature extraction involves the use of GLCM to extract texture features. Using Hybrid model is a part of training the model. With an overall accuracy 96.17%, the suggested model surpasses competitors such as CNN and GCN.

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