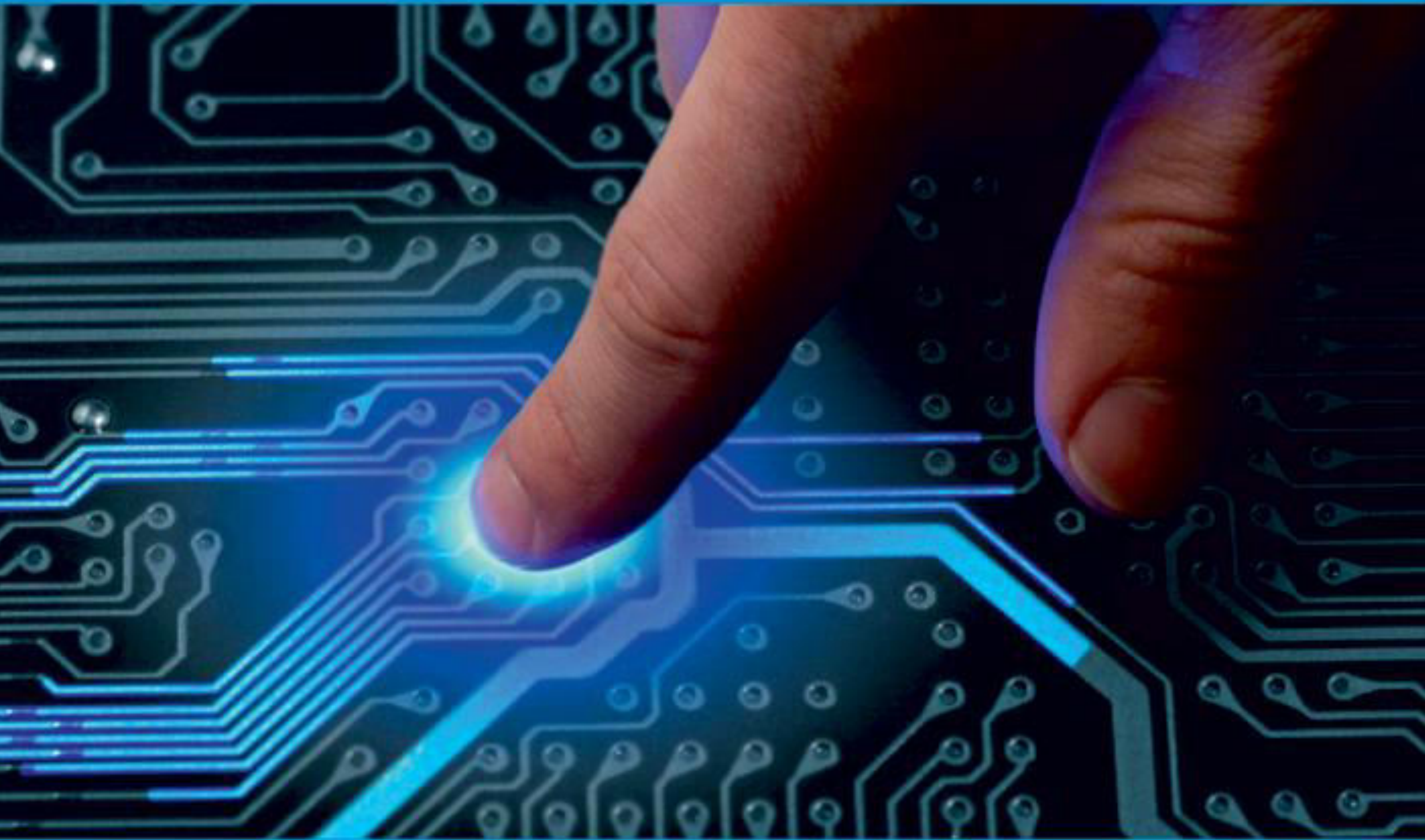
IJIRCCE

e-ISSN: 2320-9801 | p-ISSN: 2320-9798



INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN COMPUTER & COMMUNICATION ENGINEERING

Volume 12, Issue 11, November 2024

INTERNATIONAL STANDARD SERIAL NUMBER INDIA

Impact Factor: 8.625

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 8.625| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

Integrating Deep Learning and Demographic Markers for Early Detection of Anomalies in Brain Imaging: Leveraging Supervised and Unsupervised Models for Clinical Decision Support

Shwetha S[1], Bhuvana R[2], Likhith H K[3], Lakshmi M[4], Mohith P Shetty[5]

Assistant Professor, Department of Computer Engineering, CIT, Gubbi, Tumkur, Karnataka, India[1]

U.G. Student, Department of Computer Engineering, CIT, Gubbi, Tumkur, Karnataka, India[2,3,4,5]

ABSTRACT: Brain MRI analysis is vital for detecting abnormalities like tumors and neurological disorders. However, the complexity of brain structures makes manual analysis challenging, time-consuming, and error- prone. Traditional expert assessments, while essential, lack scalability and require significant expertise and resources, highlighting the need for automated solutions that deliver accurate and efficient results. Machine learning, particularly deep learning, offers promising advancements. Unsupervised anomaly detection (UAD) models are especially useful, as they can conduct preliminary assessments without large labelled datasets—a valuable benefit in medical settings where labelling is costly and resource-intensive.

KEYWORDS: Brain MRI diagnostics, Anomaly detection, Deep learning, Automated analysis, Unsupervised anomaly detection (UAD)

I. INTRODUCTION

Since the introduction of X-rays over a hundred years ago, radiology has become essential in identifying, monitoring, and planning treatment for intracranial masses. Despite remarkable progress in clinical methodologies and imaging innovations since the days of skull radiographs, the core objectives of medical imaging—achieving accurate, non-invasive diagnoses and evaluating treatment responses—remain integral to brain tumor management. MRI, a cornerstone of contemporary neuroimaging, offers detailed structural imaging while also capturing critical cellular, vascular, metabolic, and functional aspects of brain tumors, thus playing a vital role in clinical decision-making [1].

In modern medical diagnostics, particularly with brain MRI analysis, the demand for automated solutions that are both precise and efficient is growing rapidly. Manual interpretation of MRI images, while still indispensable, is a time-intensive process that requires specialized expertise and is vulnerable to human error, given the brain's complex structure. As imaging data volume increases across healthcare settings, traditional manual methods are increasingly impractical, emphasizing the need for automated systems capable of swiftly and accurately detecting abnormalities.

A significant hurdle in developing these automated tools is their reliance on labelled datasets. The annotation of medical images, especially brain MRIs where abnormalities can be nuanced and variable, is costly, labour intensive, and requires expert professionals. This challenge has encouraged a shift toward unsupervised anomaly detection (UAD) techniques, which can identify deviations from normal structures without the need for extensive labelled data.

UAD methods are designed to learn patterns representative of a healthy brain from existing data and identify anomalies—such as tumors or neurological disorders—based on deviations from these patterns. By reducing the dependency on detailed labelling of every potential abnormality, UAD facilitates more efficient preliminary assessments, allowing quicker identification of cases needing expert evaluation. This approach is especially valuable in medical imaging, where limited labelled data and the high costs of manual annotation restrict the widespread adoption of diagnostic automation.

© 2024 IJIRCCE | Volume 12, Issue 11, November 2024| DOI: 10.15680/IJIRCCE.2024.1211040

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 8.625| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

Incorporating demographic data, such as age, alongside MRI data has proven to improve the precision of anomaly detection models, particularly in neurological assessments. Age-related markers can be embedded within deep learning models, enabling more customized evaluations of brain health. This not only enhances the sensitivity of detecting anomalies but also helps distinguish between typical age-related changes and early signs of diseases. Research indicates that combining demographic information with MRI characteristics significantly enhances model performance, especially in monitoring disease progression. This integrated approach is particularly impactful in UAD scenarios with limited labeled data. For instance, UAD models that incorporate brain age estimation can sharpen the anomaly detection process, yielding more context-sensitive and accurate diagnoses in clinical settings [2].

II. LITERATURE SURVEY

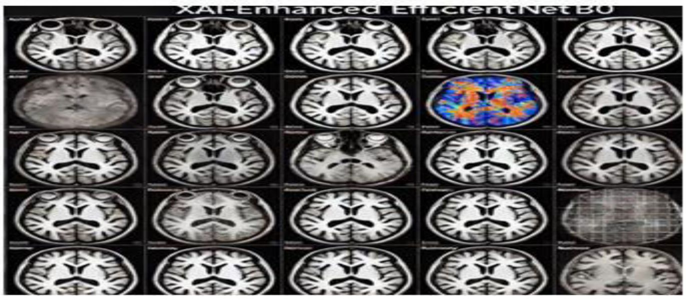
A .Supervised Learning Methods:

Deep convolutional neural networks (CNNs) are widely used in MRI brain tumor detection due to their ability to automatically learn and extract relevant features from medical images. These networks, which consist of several layers such convolutional, pooling, and fully connected layers, aid in the correct categorization of tumors by capturing complex patterns in brain MRI data. CNNs have demonstrated efficacy when used alone, but they have also been demonstrated to improve classification performance when combined with more conventional machine learning classifiers like Decision Trees (DTs), Naive Bayes (NB), and Support Vector Machines (SVMs). CNNs manage feature extraction in hybrid models, and classifiers examine these characteristics to enhance tumor identification. For example, SVMs work well with high-dimensional MRI data, assisting in the separation of tumorous and non-tumorous areas.[3]

This study examined a dataset of 3264 Magnetic Resonance Imaging (MRI) brain scans, including images of pituitary gland tumors, gliomas, meningiomas, and healthy brains. First, MRI brain pictures were subjected to preprocessing and augmentation methods. We then created a convolutional auto-encoder network and a new 2D CNN, both of which had previously been trained using the hyperparameters we had been given. Multiple convolution layers are then included in the 2D CNN; each layer in this hierarchical network has a 2*2 kernel function. Eight convolutional and four pooling layers make up this network. Batch-normalization layers were performed once all of the convolution layers were completed. A convolutional auto-encoder network and a convolutional network for classification that makes use of the final output encoder layer of the first half are both included in the updated auto-encoder network.

EfficientNet-b0 is a convolutional neural network that is trained on more than a million images from the ImageNet database The network can classify images into 1000 object categories, such as keyboard, mouse, pencil, and many animals. As a result, the network has learned rich feature representations for a wide range of images. The network has an image input size of 224-by-224.[4]

Ensemble learning is a powerful technique that combines multiple machine learning models to improve classification accuracy and robustness, especially in complex tasks like brain tumor detection and segmentation. The fundamental tenet of ensemble methods is that, in comparison to utilizing a single model, total performance can be improved by combining various models, each of which contributes unique strengths. This is especially helpful in medical imaging, where a single model might not be able to generalize well due to the frequently complicated and noisy nature of the data.



A. XAI enhanced EfficientNetB0

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 8.625| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

VS-BEAM (Variance-based Ensemble of Adaptive Models) is a noteworthy ensemble method. A variety of base classifiers, including Adaboost, Random Forest, and Extra Trees, are combined by VS-BEAM to provide a wide range of models. Despite using distinct algorithms or parameters, both models are trained on the same dataset and offer complementary insights into the data. A final classification or segmentation result is obtained by combining the predictions of the separate models after they have been trained. By taking into account several angles of view, VS-BEAM improves overall accuracy by lowering the possibility of errors from individual models. With a particular focus on variance-based learning, VS-BEAM helps to find and highlight the most pertinent features in the data, increasing the model's sensitivity to minute changes that can point to the existence of a tumor. Using the pooled knowledge of several models, the method also reduces overfitting, which can happen when one model is either simple or too complicated. Consequently, VS- BEAM has demonstrated encouraging outcomes in enhancing the segmentation of tumor locations in MRI images as well as the classification of tumor types.

When it comes to medical image analysis, ensemble approaches like VS-BEAM are particularly helpful since they can manage the intricacy and unpredictability of MRI scans better than a single model, producing predictions that are more accurate and trustworthy.

B. Unsupervised Learning and Anomaly Detection:

In the field of medical imaging, unsupervised anomaly detection techniques have drawn a lot of interest, especially for identifying anomalies like brain tumors in MRI scans without the requirement for large labelled datasets. Because these methods may detect departures from typical patterns without depending on manually annotated data—which is frequently expensive and hard to come by—they are especially useful in medical imaging

Variational Autoencoders (VAEs) and Patched Denoising Diffusion Probabilistic Models (DDPMs) are two well-known unsupervised methods for anomaly identification. Both approaches make use of deep learning's capabilities to model typical data patterns and then discover anomalies by spotting notable departures from the learnt distribution.

1. One kind of generative model that learns a probabilistic mapping between high-dimensional input (such as MRI scans) and a lower-dimensional latent space is called a variational autoencoder (VAE). Modelling the underlying structure of "normal" data in this latent space is the main goal of VAEs. The model learns to encode images of the healthy brain into a compact representation when it is trained on these images. The VAE recognizes a new MRI picture as an anomaly during inference if it differs noticeably from this learned distribution. Without labelled data, this method works well for identifying anomalous brain structures like cancers. VAEs are powerful because they can provide reconstructions of the input data, and abnormalities are indicated by high reconstruction errors.[5]
2. Patched Denoising Diffusion Probabilistic Models (DDPMs): In unsupervised anomaly detection tasks, diffusion models— in particular, DDPMs—have demonstrated encouraging outcomes. In order for these models to recreate the original data, they first learn to gradually convert the data—in this example, MRI images—into random noise. By first diffusing the normal data to noise and then reversing the change, the model learns the distribution. When the reconstruction error is large, the model can identify abnormalities in the context of brain tumor identification, indicating that the image does not correspond to the typical pattern that was learned during training. DDPMs are very good at identifying localized abnormalities, including tumors in certain brain regions, because they can concentrate on local features by segmenting the image into smaller patches.[6]

C. GANs (Generative Adversarial Networks)

In the field of medical image analysis, Generative Adversarial Networks (GANs) have become a potent tool, especially for identifying abnormalities in imaging data, like brain MRIs. Two neural networks—a discriminator and a generator—that are trained concurrently in a competitive manner make up the GAN class of deep learning models. While the discriminator compares these images to real data and learns to differentiate between real and synthetic samples, the generator produces synthetic data that looks like real photos. The discriminator gets better at telling the difference between actual and phony images over time, and the generator gets better at creating realistic images.

1. **Normal Image Distribution Learning:** To comprehend the statistical and structural patterns of normal anatomy, GANs are trained on a sizable dataset of photographs of healthy brains. The generator gains the ability to create artificial MRI pictures that closely resemble these typical patterns. Throughout the training process, the discriminator gains the ability to recognize and categorize these produced images as "real" (based on the training data) or "fake"

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 8.625| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

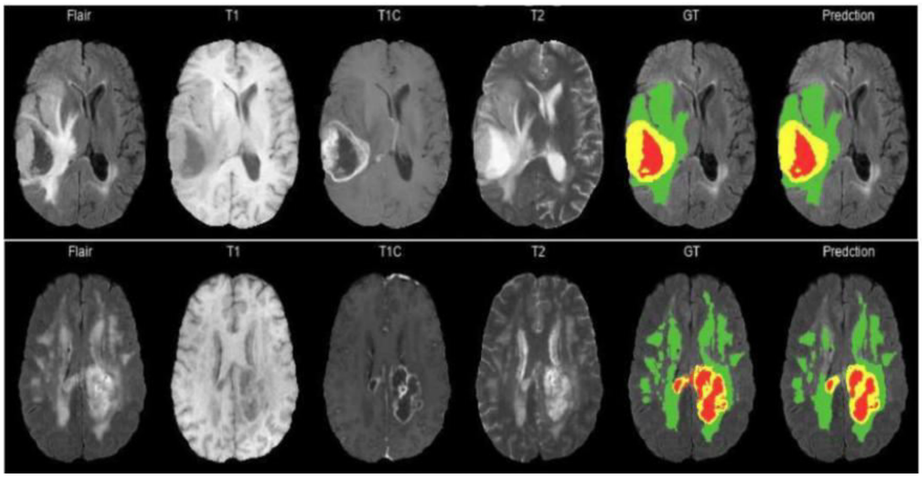
(produced by the model). The generator becomes more adept at simulating typical MRI images through this adversarial process, which makes it a good tool for spotting deviations.[7]

2. Anomaly Detection Mechanism: New MRI pictures can be assessed by the GAN following training. The discriminator is used to evaluate the new image and determine how well it matches the distribution of normal brain structure that has been taught. It is more likely to be marked as an anomaly if the new image has an anomaly (like a tumor) because it will not fit in well with the distribution of normal photos. Because it can identify minor, invisible irregularities without annotated instances in the dataset, this method is especially beneficial because it eliminates the need for explicit annotations for each sort of anomaly.[7]

III. METHODOLOGY

A. Data collection:

A publicly accessible resource created especially for medical image analysis is the BraTS 2019 dataset. It includes annotated MRI scans, which are mostly utilized for supervised learning activities, especially when it comes to segmenting brain tumors. A range of brain MRI scans with labels that categorize various tumor tissue types (such as enhancing tumor, necrotic tumor, and edema) are included in this collection. It is an essential tool for developing machine learning models that increase the precision of automatically detected brain tumors. Healthy MRI scan datasets are frequently used for unsupervised learning. Models are trained using these datasets so they can identify patterns or abnormalities without the need for labeling. For tasks like anomaly detection or segmentation, where the lack of labels enables more generalized learning, as well as for training models to comprehend normal brain structure, healthy MRI data are essential.[8]



B. BraTS 2019 dataset

B**. Preprocessing Techniques:**

1. Noise reduction: Medical images can be distorted by noise, making it more difficult to spot important details. In order to smooth the image and eliminate random noise, Gaussian blur or median filtering are frequently used. Another cutting-edge method that minimizes noise while maintaining crucial features is Non-Local Means Denoising (NLM).[9]

2. Contrast Enhancement: Images with higher contrast can more easily distinguish between different tissues. Contrast Limited Adaptive Histogram Equalization, or CLAHE, is a widely used technique. By using histogram equalization in smaller sections of the image, it enhances features in textured areas while decreasing noise in uniform areas, improving local contrast. When there are slight variations between tumor and normal tissue, this is especially beneficial.

3. Cropping and Resizing: To highlight areas of interest, such a particular brain region in tumor identification, unnecessary portions of a picture can be cropped in medical imaging. In order to make images suitable for model input, scaling makes sure they are the same size. For neural networks, this usually means resizing to predetermined dimensions, such as 224x224 pixels.

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 8.625| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

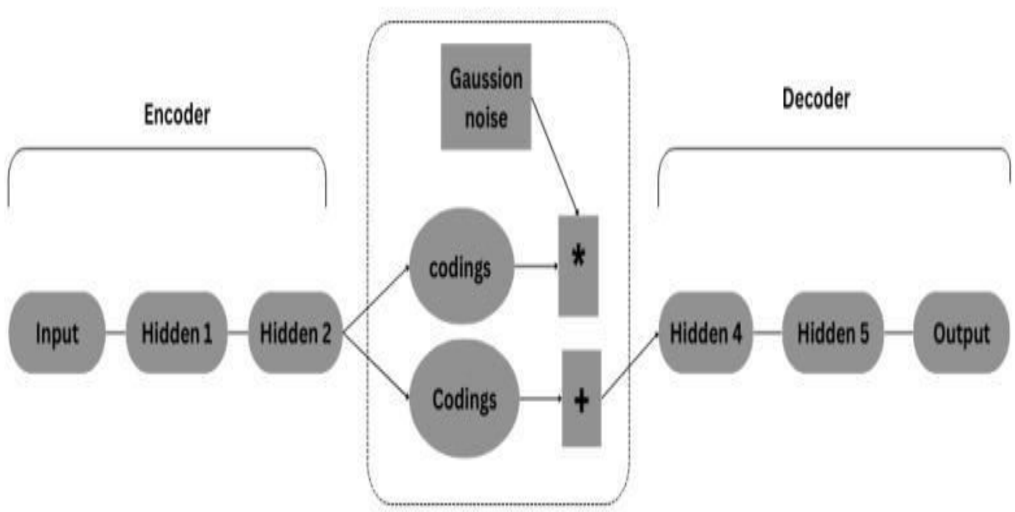
C. Model selection:

1. supervised model

Recommended Techniques: EfficientNet-B0: Known for its high accuracy and computation efficiency, EfficientNet-B0 is a cutting-edge convolutional neural network (CNN). It is appropriate for jobs like brain tumor classification, where high accuracy is essential in recognizing tumors at different stages, because it uses a compound scaling method to balance depth, width, and resolution.[10] CNN + KNN: This hybrid approach combines CNN for feature extraction with KNN (K-Nearest Neighbours) for classification. CNN offers both robust feature extraction and straightforward classification by extracting deep features from MRI images and using KNN to accomplish the final classification based on similarity to other data points.

2. Unsupervised model

Variational Autoencoder with Age Prediction, or VAE-ap, is an unsupervised method that uses MRI data to simulate the aging patterns of the brain. In order to comprehend atypical brain problems, it incorporates brain age as a consideration, which can be quite important. By learning the distribution of brain ages and spotting variations that might point to pathological alterations, the VAE-ap assists in anomaly detection. Denoising Diffusion Probabilistic Models, or "patched DDPMs," are models that can be used to detect anomalies locally. To find anomalous areas, the image is separated into patches, and each patch is processed separately using diffusion models. This technique works well for locating localized anomalies, like tiny brain lesions or tumors.



C. Variational Autoencoder

IV. IMPLEMENTATION

A. Data augmentation

The process of producing altered versions of preexisting photographs in order to artificially increase the dataset's size is known as data augmentation. It enhances model generalization, particularly in medical imaging, where it might be difficult to acquire a lot of labeled data. Typical enhancement techniques consist of:

Rotations: By rotating images at different angles (such as 90° and 180°), the model is able to identify characteristics from a variety of viewpoints.

Flipping: By reducing the model's sensitivity to image orientation, horizontal and vertical flips improve robustness.

Scaling: Variability is introduced by slightly increasing or decreasing images, which helps the model learn invariant properties.[11]

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 8.625| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

B. Training and Optimization

The model gains the ability to map input MRI pictures to accurate abnormalities or classifications during training. Hyperparameter tweaking and optimizers are essential components of this procedure:

Optimizers: Because of its effectiveness with sparse gradients and adjustable learning rates, the ADAM (adjustable Moment Estimation) optimizer—which combines the advantages of RMSProp and Stochastic Gradient Descent (SGD)—is frequently utilized for EfficientNet. Because ADAM is adaptable, it accelerates convergence and works well for challenging tasks like classifying medical images.

Hyperparameter Tuning: To maximize model performance, key parameters including learning rate, batch size, and number of epochs are adjusted. To improve the model's capacity for generalization, the optimal combination of these values can be found, for instance, using grid search or Bayesian optimization.[12]

C. Model fine tunning

When using pre-trained models, such as EfficientNet-B0, to domain-specific tasks, such brain tumor classification, fine-tuning is crucial:

Transfer Learning: EfficientNet-B0 has acquired general picture features after being first trained on extensive datasets such as ImageNet. These pre-trained weights provide a solid starting point for transfer learning, which entails fine-tuning the network on the target MRI dataset. In order to teach later layers to recognize task-specific features in the MRI data, "freezing" previous layers—which record broad features— is a must.

Layer Adjustment: To enable fine-grained modifications, certain layers may occasionally be unfrozen or new layers may be added. This guarantees that the model retains generic features acquired from larger datasets while becoming sensitive to MRI-specific patterns.[13]

V. CONCLUSION

This study demonstrates how deep learning models, unsupervised learning techniques, and demographic markers—like estimated brain age—can be combined to improve the accuracy of anomaly identification in medical imaging. The algorithms collect subtle information from MRI scans and combine them with individualized patient data using a hybrid approach that combines supervised and unsupervised learning approaches. This results in more precise, context-sensitive anomaly diagnosis. Small brain tumors or early indicators of neurodegenerative diseases are examples of minor but clinically relevant anomalies that can be detected using this layered approach that would otherwise go unnoticed by traditional analysis techniques. Specifically, using brain age as a demographic indicator offers a useful starting point for identifying abnormalities in brain structure and function that are linked to age-related illnesses or early aging trends. When paired with deep learning, these models are able to more sensitively examine brain MRIs, comparing the estimated and real ages of the brain to identify any growth abnormalities or unique symptoms of degeneration that might indicate underlying pathology. The therapeutic implications of this strategy are significant since it may enable prompt actions and result in earlier, more accurate diagnosis. By helping physicians make well-informed decisions, these models' customized predictions may help lower diagnostic errors and direct treatment choices. Because of this, this integrated approach not only improves diagnostic skills but also fosters patient-centered care, opening the door to proactive and individualized treatment programs that lead to better health outcomes. In the end, this strategy provides a positive path for upcoming developments in medical imaging, encouraging more adaptable, data-driven treatment procedure

REFERENCES

[1] https://pmc.ncbi.nlm.nih.gov/articles/PMC5581219/-national library of medicine

[2] https://ar5iv.labs.arxiv.org/html/2111.14388 - AR5IV

[3] **Tan, M., & Le, Q. V. (2019).** "EfficientNet: Rethinking model scaling for convolutional neural networks." *Proceedings of the 36th International Conference on Machine Learning*, 97, 6105-6114.

[4] https://www.mathworks.com/help/deeplearning/ref/efficientnetb0.html

[5] Kingma, D. P., & Welling, M. (2014). Auto-Encoding Variational Bayes. *arXiv:1312.6114*.

[6] Song, Y., & Ermon, S. (2019). Generative Modeling by Estimating Gradients of the Data Distribution. *arXiv:1907.05600*.

[7] *In Advances in neural information processing systems (pp. 2672-2680)*. Retrieved from https://arxiv.org/abs/1406.2661.

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 8.625| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

[8] Bakas, S., Akbari, H., et al. (2019). "Segmentation of Brain Tumor in MRI: BraTS 2019 Challenge." Brain Tumor Segmentation Challenge (BraTS) 2019. URL: https://www.medicaldecathlon.com.

[9] Tustison, N. J., et al. (2010). "N4ITK: Improved N3 Bias Field Correction." *IEEE Transactions on Medical Imaging*.

[10] Tan, M., & Le, Q. V. (2019). "EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks." *In Proceedings of the 36th International Conference on Machine Learning (ICML)*.

[11] Shorten, C., & Khoshgoftaar, T. M. (2019). "A survey on image data augmentation for deep learning." *Journal of Big Data, 6*(1).

[12] Kingma, D. P., & Ba, J. (2014). "Adam: A method for stochastic optimization." *arXiv preprint arXiv:1412.6980*.

[13] Pan, S. J., & Yang, Q. (2010). "A survey on transfer learning." *IEEE Transactions on Knowledge and Data Engineering, 22*(10)

INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN COMPUTER & COMMUNICATION ENGINEERING