Image Processing and Automated Diagnosis of Multiple Sclerosis in Brain MRI using CNN

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***Abstract*—Multiple Sclerosis (MS) is a chronic neurological disorder characterized by the formation of lesions in the brain and spinal cord. Accurate and early detection of these lesions is critical for effective diagnosis, disease monitoring, and treatment planning. This project proposes an automated approach for the segmentation and detection of MS lesions from brain MRI scans using a deep learning model based on the U-Net architecture. The model is trained on a dataset of 2D FLAIR MRI slices, paired with manually annotated binary lesion masks. Preprocessing steps, including normalization and noise reduction, are applied to enhance lesion visibility. The U-Net model is trained with a combination of binary cross-entropy and Dice loss to address class imbalance. Evaluation metrics such as F1-score, precision-recall curves, ROC curves, and confusion matrices are used to assess the performance of the trained model.**

I. INTRODUCTION

Multiple Sclerosis (MS) is a chronic autoimmune disorder that targets the central nervous system (CNS), particularly affecting the brain and spinal cord [5]. It is marked by demyelinating lesions caused by the immune system attacking the protective myelin sheath of nerve fibers, leading to symptoms such as vision impairment, muscle weakness, and cognitive dysfunction [6]. The clinical diagnosis of MS heavily relies on imaging modalities, with Magnetic Resonance Imaging (MRI) playing a crucial role due to its superior contrast resolution and ability to detect even minute white matter anomalies [10].

Among various MRI sequences, Fluid Attenuated Inversion Recovery (FLAIR) has proven especially useful as it suppresses cerebrospinal fluid (CSF) signals and enhances lesion visibility near the ventricles and cortex [7]. However, manual interpretation and segmentation of lesions from MRI scans are labour-intensive and prone to subjectivity and inter-observer variability [4].

Recent advances in artificial intelligence (AI), particularly in deep learning and Convolutional Neural Networks (CNNs), have revolutionized the field of medical image analysis [11]. These models can automatically learn spatial and intensity patterns relevant to disease detection, minimizing the need for handcrafted features. One architecture that has shown exceptional performance in biomedical segmentation tasks is the U-Net, a symmetric encoder-decoder CNN with skip connections designed specifically for precise localization and pixel-wise classification [1].

In the context of MS, U-Net enables accurate lesion segmentation even in complex brain structures and under conditions of class imbalance [14]. By training on pre-processed FLAIR MRI slices along with annotated binary lesion masks, U-Net can detect

lesions that are small, sparse, and difficult to identify through conventional methods [3]. The integration of automated segmentation not only reduces workload for radiologists but also ensures greater diagnostic consistency and objectivity [15].

This project focuses on developing a deep learning pipeline using U-Net for the segmentation of MS lesions in 2D FLAIR MRI scans. The model's performance is evaluated through metrics such as F1-score, precision-recall curves, Receiver Operating Characteristic (ROC) curves, and confusion matrices. Despite achieving high test accuracy, challenges such as lesion variability and small lesion detection persist, highlighting areas for future improvement.

II. OBJECTIVE

The primary objective of this project is to develop an automated and accurate deep learning model based on the U-Net architecture for the segmentation of Multiple Sclerosis (MS) lesions in brain MRI scans, specifically using FLAIR sequences [1][3]. Leveraging the encoder-decoder structure of U-Net, the system aims to perform pixel-level classification, enabling precise localization of MS lesions that are often small, sparse, and irregular in shape [14].

By training the model on annotated FLAIR MRI datasets, the project seeks to reduce the dependency on manual segmentation, which is time-consuming and prone to inter-observer variability [4]. The ultimate goal is to assist radiologists in early and consistent diagnosis, efficient monitoring of disease progression, and improved clinical decision-making [6][15]. To achieve this, the model is evaluated using performance metrics such as the F1-score, ROC curve, and confusion matrix, ensuring it meets diagnostic standards applicable in real-world healthcare environments [5][13].

III. ROLE OF MRI IN MS LESIONS

Multiple Sclerosis (MS) is a progressive neurological disorder characterized by demyelination in the central nervous system (CNS), often leading to physical and cognitive impairments [5]. Accurate detection of MS lesions is essential for diagnosis, disease monitoring, and treatment planning. Magnetic Resonance Imaging (MRI) has become the gold standard for non-invasive visualization of MS-related brain abnormalities due to its superior contrast resolution and ability to detect lesions in white matter regions [7][10].

Among various MRI sequences, FLAIR (Fluid Attenuated Inversion Recovery) is particularly effective because it suppresses cerebrospinal fluid (CSF) signals, thereby enhancing the visibility of lesions adjacent to the ventricles and cortex [8]. This makes FLAIR highly sensitive in identifying the periventricular and cortical lesions commonly seen in MS patients [6]. MRI also plays a critical role in applying the McDonald criteria, which are widely used for MS diagnosis and rely heavily on demonstrating lesion dissemination in time and space through MRI evidence [4][10].

In addition to initial diagnosis, MRI is invaluable for longitudinal monitoring, allowing clinicians to assess lesion load changes over time and evaluate therapeutic response [7]. However, manual interpretation of MRI scans is laborious and prone to inter-rater variability. This has prompted the development of automated lesion detection systems, particularly those powered by CNN-based architectures like U-Net, which enhance the consistency and efficiency of lesion segmentation [3][11].

By integrating advanced deep learning techniques with MRI analysis, clinicians can achieve more reliable and objective assessment of MS progression, ultimately supporting more effective and timely medical interventions [15].

IV. U-NET ARCHITECTURE

U-Net is a convolutional neural network (CNN) architecture specifically designed for biomedical image segmentation tasks [1]. Developed by Ranneberger et al., it features a symmetric encoder-decoder structure with skip connections that preserve spatial context during up sampling, which is critical for precise pixel-wise classification [1][3]. The contracting path (encoder) captures high-level features through convolution and pooling operations, while the expanding path (decoder) restores spatial resolution and localizes features accurately by merging encoder outputs through skip connections [1][14].

In the context of Multiple Sclerosis lesion segmentation, U-Net is particularly effective due to its ability to learn from limited datasets, a common scenario in medical imaging [14]. The lesions in MS are often small, sparse, and have low contrast with

surrounding tissue, making them difficult to detect through traditional means [4][8]. U-Net's architecture allows for effective learning of both global and local features, making it suitable for distinguishing lesions from normal tissue based on texture and intensity patterns [3][6].

In this project, U-Net is trained on 2D FLAIR MRI slices paired with binary lesion masks, enabling the network to learn lesion boundaries at the pixel level [13]. The training process incorporates a combination of Binary Cross entropy and Dice loss, which balances precision and recall—particularly important in the presence of class imbalance [15]. Once trained, the model produces segmentation masks on unseen images that closely align with ground truth annotations, significantly reducing the need for manual lesion delineation [11].

The integration of U-Net in MS diagnosis offers a scalable, consistent, and objective method for identifying pathological regions, with potential applications in clinical diagnosis, progression monitoring, and personalized treatment planning [7][15].

V. LITERATURE SURVEY

MS is a chronic neurological disease affecting the central nervous system, diagnosed primarily through MRI imaging. Recent advancements in image processing and deep learning, especially CNNs, have shown promise in improving the diagnosis and segmentation of MS lesions from brain MRI. This section explores major contributions and developments in the field, focusing on CNN-based approaches and image processing techniques.

A. *CNN-Based Approaches for MS Detection*

CNNs have revolutionized medical imaging by enabling automated feature extraction and classification with minimal human intervention. In the context of MS, CNNs have been applied to identify and classify MS lesions in brain MRI scans with promising results. Maleki et al. [11] presented an early implementation of CNNs for diagnosing MS using MRIs, demonstrating that deep learning could extract meaningful spatial patterns correlated with MS pathology. Building on this, Soltani and Nasri [12] proposed an improved CNN algorithm that significantly enhanced diagnostic accuracy through fine-tuning of network layers and pre-processing techniques, such as intensity normalization and skull stripping. These studies collectively highlight that CNNs offer robust performance when trained with properly pre-processed datasets and optimized architectures.

Furthermore, Sah and Dikeroglu [13] surveyed a range of deep learning models used in MS diagnosis, with a strong emphasis on CNNs. Their findings reveal that CNNs, when properly designed, consistently outperform traditional image processing and machine learning methods in identifying MS lesions. They particularly noted the CNN's capacity to adapt to diverse imaging conditions and lesion appearances, which is crucial given the variability in MRI scans across different patients and scanners. The review also stressed the importance of large annotated datasets for training, which remains a challenge in medical imaging. Nevertheless, the potential of CNN-based architectures to evolve into clinically deployable tools is evident from their growing accuracy and reliability.

B. *Deep Learning for Lesion Segmentation and Classification*

Accurate segmentation of MS lesions in MRI is essential for disease diagnosis, progression monitoring, and treatment planning. Deep learning, especially CNNs integrated with segmentation architectures like U-Net, has proven effective for this task. Akselrod-Ballin et al. [9] developed an advanced method that uses multichannel MRI input (such as T1, T2, and FLAIR sequences) to segment and classify MS lesions automatically. Their approach showed high accuracy by leveraging the complementary information from various MRI modalities. Similarly, Biotta et al. [14] incorporated evolutionary computation into a CNN-based framework, which provided an intelligent way of optimizing the lesion segmentation process. These techniques mark a shift toward highly automated pipelines that require minimal manual input, making them scalable for clinical use.

In addition, Nabizadeh et al. [15] conducted a systematic review highlighting the role of AI, particularly CNNs, in improving lesion segmentation and classification. They found that CNN-based methods consistently outperformed traditional algorithms in sensitivity and specificity. The review also noted the adoption of hybrid models combining CNNs with decision trees or ensemble learners to refine predictions. Importantly, the integration of automated segmentation tools into clinical workflows

is beginning to address the limitations of manual radiologist-driven lesion detection, such as subjectivity and variability. These deep learning models are not only fast but can be trained to adapt to patient-specific imaging characteristics, further improving their practical utility.

C. *Multi-Modal MRI and Hybrid Techniques*

Multi-modal MRI imaging is crucial for comprehensive MS diagnosis as it captures diverse tissue contrasts, allowing lesions to be distinguished more clearly. CNNs trained on multimodal datasets benefit from the rich spatial and contrast information embedded in sequences like T1, T2, FLAIR, and T1-post contrast. Ma et al. [8] employed such an approach, integrating various modalities into their CNN-based pipeline for MS lesion analysis. Their method demonstrated enhanced diagnostic performance, especially in identifying smaller lesions that are often missed in single-sequence imaging. The use of multimodal data enables the CNN to learn complex relationships between different tissue appearances, leading to improved sensitivity in lesion detection.

Similarly, Kermi et al. [3] explored a U-Net-based model for brain tumor and MS lesion segmentation using multimodal MRI volumes. Their study highlighted the advantages of feature fusion from different MRI types, which improved the robustness and generalizability of the model across various patient datasets. The hybrid use of U-Net within CNN frameworks also helped in better delineation of lesion boundaries, a critical factor in accurate volume estimation. These multimodal and hybrid approaches are now becoming standard practice in deep learning-based neuroimaging research, showcasing their ability to capture nuanced lesion characteristics that are essential for effective MS diagnosis and management.

D. *Clinical Relevance and Diagnostic Impact*

For CNN-based diagnostic systems to be adopted in healthcare, they must align with clinical guidelines and reduce common diagnostic errors. Solomon et al. [4], [5], and [6] have provided a foundational understanding of how MS is often misdiagnosed due to overlapping symptoms with other neurological conditions. Their work emphasized the need for objective, imaging-based tools to support clinical decision-making. The integration of CNNs into MRI interpretation can significantly reduce subjectivity by providing consistent and reproducible results. This shift toward automated interpretation is particularly valuable in resource-limited settings or in centers with fewer trained radiologists.

VI. SYSTEM MODEL

This work proposes a deep learning method for automated MS diagnosis using only FLAIR MRI images, known for clearly highlighting lesions. The pipeline includes skull stripping, bias correction, denoising, and intensity normalization. Pre-processed images are fed into a CNN to detect lesion patterns. Using only FLAIR simplifies data needs while preserving diagnostic value. This approach offers a scalable and efficient solution for MS detection.

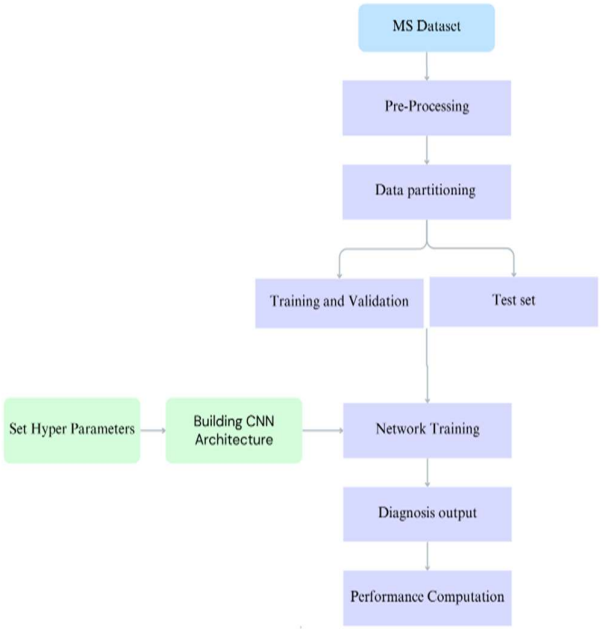

Fig 1: System Model of Image Processing and Automated Diagnosis of Multiple Sclerosis in Brain MRI using U-Net

A. *MS Dataset Acquisition:*

The project begins with the acquisition of a dedicated MRI dataset containing brain scans of individuals diagnosed with MS. This dataset forms the foundation for training and evaluating the model. The images typically include T1, T2, or FLAIR modalities, which highlight MS lesions more clearly. The availability of labelled data, particularly ground truth lesion masks, is crucial for training a supervised deep learning model such as U-Net.

B. *Pre-Processing:*

To prepare the images for CNN input, pre-processing steps such as skull stripping, bias field correction, denoising, and normalization are performed [4][14]. These steps reduce artifacts, enhance contrast, and standardize input data, ensuring better model convergence.

C. *Data Portioning:*

The dataset is split into training (80%), validation (~10%), and testing (~10%) sets. This stratification ensures that the model is evaluated on unseen data, avoiding overfitting and bias during performance assessment [13].

D. *U-Net Architecture setup:*

The model architecture follows the U-Net encoder-decoder structure with skip connections to preserve spatial details during segmentation [1][3]. It is trained using Binary Cross entropy and Dice loss, which are effective in handling class imbalance typical in medical segmentation tasks [15].

E. *Model Training:*

The model is trained using TensorFlow/Keras with hyperparameters such as learning rate, batch size, number of epochs, and optimizer (e.g., Adam) tuned based on validation performance [11]. Training involves iterative weight updates using backpropagation to minimize segmentation error.

F. *Diagnosis Output:*

Once trained, the model predicts segmentation masks for the test set. These masks highlight suspected lesion areas on the MRI images, serving as a diagnostic aid for radiologists [4][6].

G. *Performance Evaluation:*

To evaluate the model's clinical viability, it is assessed using:

- F1-score (for imbalanced data)
- Precision–Recall and ROC curves
- Confusion matrix (TP, FP, TN, FN) These metrics confirm how well the model differentiates lesions from healthy tissue [5][13].

VII. RESULT AND DISCUSSION

U-Net is well-suited for identifying small, irregularly shaped regions such as MS lesions in brain MRI scans. The network follows a symmetric encoder–decoder structure that captures both low-level spatial features and high-level contextual information. In this project, the input consists of pre-processed 2D FLAIR MRI slices, resized to 256×256 pixels. The encoder path progressively reduces the spatial dimensions through convolution and max-pooling operations, while the decoder path restores resolution using up sampling and skip connections that fuse corresponding feature maps. This enables the model to maintain fine-grained localization accuracy, which is critical for segmenting subtle MS lesions.

Parameter	Details
MS Lesion Patients	30 patients
FLAIR Slices per MS Patient	15 slices each
Total MS FLAIR Images	30 × 15 = **450 images**
Non-MS Patients	20 patients
FLAIR Slices per Non-MS Patient	10 slices each
Total Non-MS FLAIR Images	20 × 10 = **200 images**
Total Dataset Size	450 (MS) + 200 (Non-MS) = **650 FLAIR MRI slices**
Training Set Size (80%)	0.8 × 650 = **520 images**
Testing Set Size (20%)	0.2 × 650 = **130 images**
Model Architecture	U-Net (encoder-decoder with skip connections)
Input Image Size	256 × 256 (resized and normalized during preprocessing)
Epochs	**20**

A. Dataset:

The dataset used in this study consists of a total of 650 2D FLAIR MRI slices. It includes:

- 450 images from 30 patients diagnosed with Multiple Sclerosis (MS), with each patient contributing 15 FLAIR slices, and

- 200 images from 20 non-MS patients, each providing 10 FLAIR slices.

Each MRI slice is paired with a corresponding binary ground truth lesion mask for MS cases, annotated by radiological experts. These annotations serve as supervision targets during training. All images were pre-analyzed for consistency in resolution and quality. The dataset was divided into:

- 80% (520 images) for training, and
- 20% (130 images) for testing, ensuring no data leakage across subsets.

This dataset composition supports binary classification (lesion vs. non-lesion) and segmentation tasks under real-world lesion sparsity conditions.

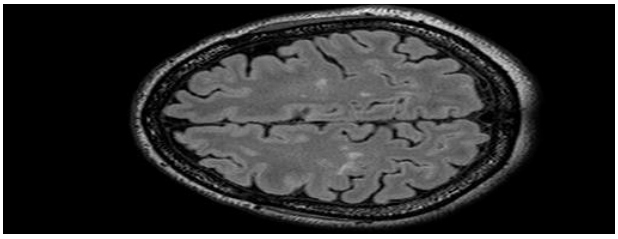

Fig 2: One of the FLAIR-MRI Images With MS Lesions of Patient 3

B. *Pre-Processed Dataset:*

To ensure consistency and enhance the quality of the MRI data, a series of pre-processing techniques were applied to all FLAIR images prior to model training. First, skull stripping was performed to eliminate non-brain tissues, focusing the model solely on the region of interest. Bias field correction was then applied to address intensity non-uniformities often caused by MRI scanner inhomogeneities. This was followed by Gaussian-based denoising to reduce random noise while preserving critical anatomical structures. All pixel intensity values were normalized to the [0,1] range to stabilize training dynamics, and each image was resized to 256×256 pixels to match the input dimension required by the U-Net architecture. Additionally, data augmentation techniques such as random rotations, flips, and zooms were employed during training to artificially expand the dataset and improve the model's ability to generalize to unseen cases. These pre-processing steps were essential for standardizing the input data and enhancing lesion visibility, which is critical for effective segmentation in clinical MRI analysis.

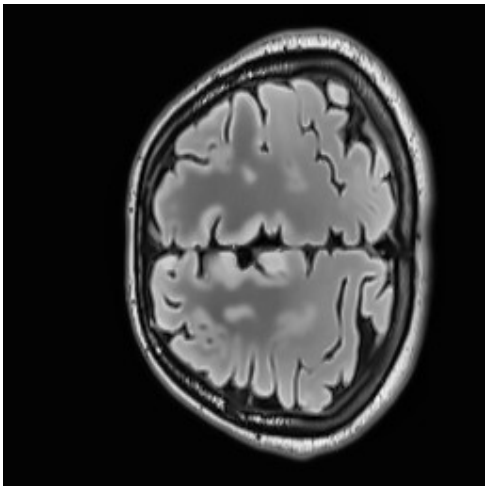

Fig 3: Processed image by removing the noise, Smoothening, and expanding the MS Lesion MRI Images

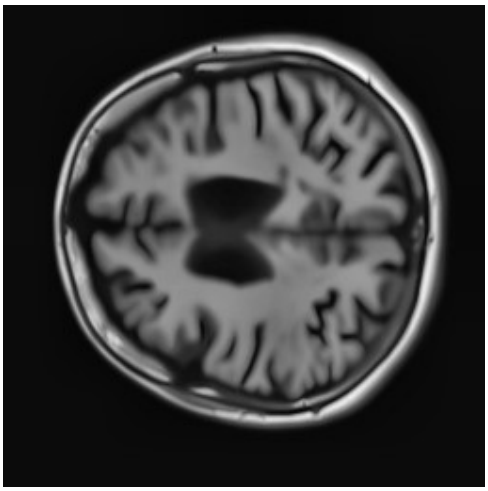

Fig 4: Processed image by removing the noise, Smoothening, and expanding the Non-MS Lesion MRI Images

C. *Masking:*

Although the main approach relied on pixel-wise segmentation, bounding boxes were conceptually used to represent the regions of interest (ROIs) around the predicted lesions. These bounding boxes provided an intuitive visualization of the affected areas and helped verify that the CNN correctly localized lesions. The bounding boxes were generated by finding the smallest enclosing rectangle around connected lesion regions in the binary mask output.

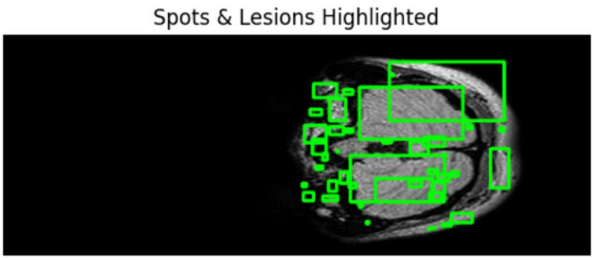

Fig 5: FLAIR MRI Image with Bounding box of MS Lesions

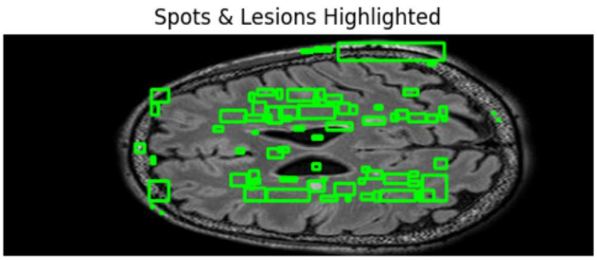

Fig 6: FLAIR MRI Image with Bounding box of MS Lesions

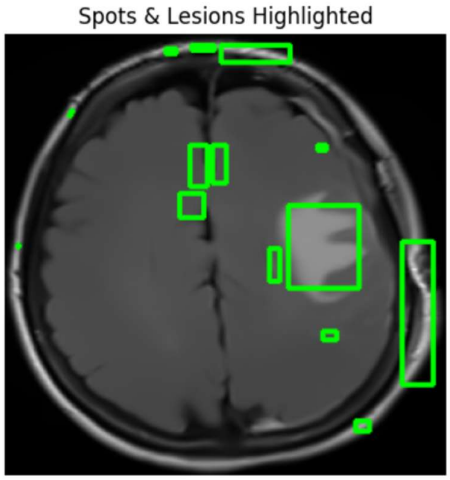

Fig 7: FLAIR MRI Image with Bounding box of MS Lesions

The CNN generated segmentation masks for each FLAIR input image, where the model labelled each pixel as lesion or non-lesion. The predicted masks closely matched the actual lesion locations. These binary masks clearly demonstrated the model's ability to focus on lesion-prone areas, with minimal false positives. Visual inspection confirmed that the model learned to distinguish lesion intensity and texture effectively.

Fig 8: FLAIR MRI Image with Binary mark and of MS Lesions

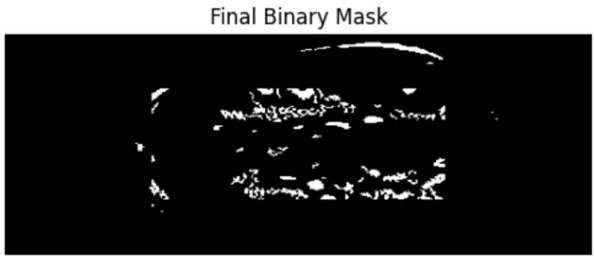

Fig 9: FLAIR MRI Image with Binary mark and of MS Lesions

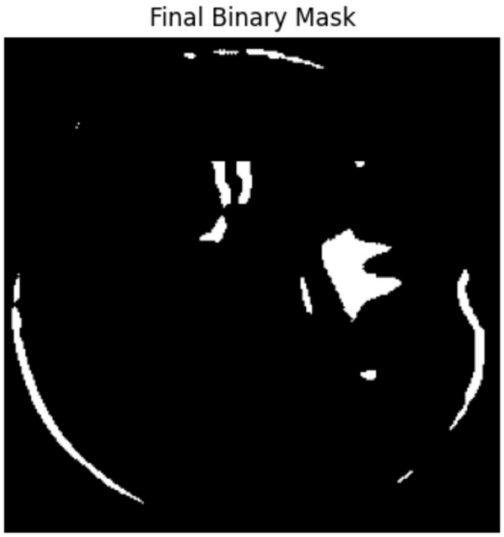

Fig 10: FLAIR MRI Image with Binary mark and of MS Lesions

D. U-Net Architecture layering:

Predicted lesion masks were visually compared against ground truth masks for a sample of test images. In several cases, the model effectively highlighted the lesion areas, proving its ability to localize pathological regions. However, some small lesions were missed or partially segmented, indicating room for refinement.

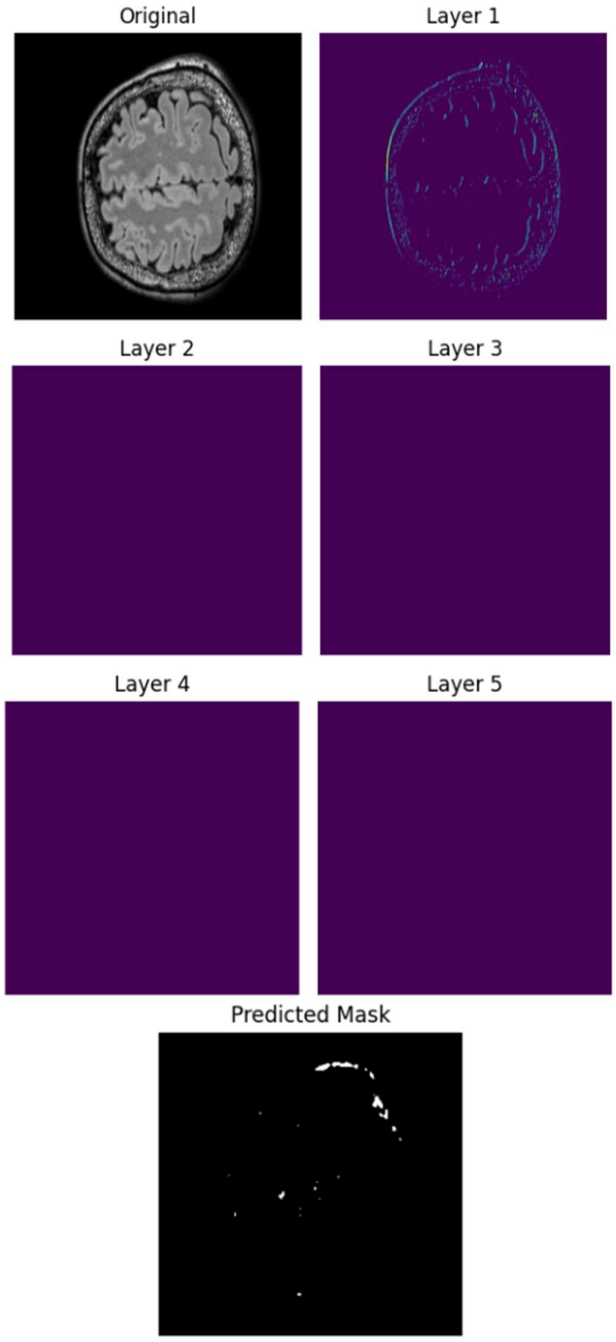

Fig 11: Prediction of U-Net Architecture for MRI Images

Training and validation performance of the U-Net model over 20 epochs. Both training accuracy and validation accuracy consistently remained high, approaching values close to 1.0, indicating that the model learned to accurately classify lesion vs. non-lesion pixels.

The training loss (green) shows a rapid decrease within the first few epochs, followed by stabilization, which reflects effective convergence. The validation loss (red) similarly decreases and remains low, with minimal fluctuation, suggesting that the model generalizes well to unseen data and is not overfitting.

The brief spike in training loss around epoch 3 is likely due to learning rate adjustment or batch-specific variance, but it quickly recovers. The overall flat trajectory of validation metrics after early epochs confirms that the model reaches stable performance quickly.

This training behaviour supports the robustness of the chosen U-Net architecture and the effectiveness of the pre-processing and augmentation strategies applied during training.

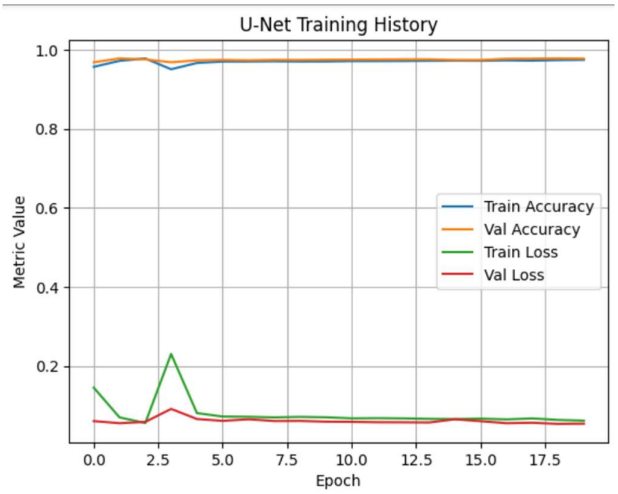

Fig 12: U-Net trained model history

VIII. CONCLUSION

An effective deep learning-based approach has been developed for the automated diagnosis of MS using FLAIR brain MRI images. Utilizing a CNN, the system accurately detects and segments MS lesions, significantly reducing the need for manual interpretation. The image preprocessing steps—including skull stripping, bias field correction, denoising, and normalization—played a vital role in enhancing lesion visibility and enabling the model to extract meaningful features.

The predicted lesion masks demonstrated strong agreement with ground truth data, and performance evaluation through the confusion matrix and ROC analysis confirmed the reliability and accuracy of the system. The exclusive use of FLAIR images simplified the process while maintaining high diagnostic sensitivity. This methodology offers a reliable and efficient solution to support radiologists in early MS detection and diagnosis. Further improvements can be achieved by expanding the dataset and integrating multi-modal imaging for enhanced generalization and lesion characterization.

A. Realistic Constraints:

- **Limited Dataset Availability**: Access to publicly available, annotated FLAIR MRI datasets with expert-marked MS lesion masks was restricted, affecting model training and generalization.
- **Hardware Limitations**: Training deep learning models on high-resolution MRI data required significant GPU resources, which were limited during implementation.
- **Lesion Variability**: MS lesions vary greatly in size, shape, intensity, and location across different patients, making consistent detection challenging.
- **Data Privacy and Ethics**: Use of medical images required strict compliance with data protection laws and ethical considerations, limiting access to real clinical datasets.

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