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Enhancing Performance of Deep Learning Models for Epilepsy Seizure Detection

Riyazulla Rahman J[1], Dr. Nagaraja S R[2]
[1]Research Scholar, Assistant Professor, School of Computer Science & Engineering
Presidency University,
Bangalore, 560064, India.
e-mail: riyaz@presidencyuniversity.in
[2]Associate Professor, School of Computer Science & Engineering
Presidency University,
Bangalore, 560064, India.
e-mail: nagarajasr@presidencyuniversity.in

Abstract

Epilepsy is a neurological condition marked by recurring seizures, leading to notable effects on the well-being of individuals experiencing it. Deep learning models have shown promising results in detecting and classifying epilepsy based on electroencephalogram (EEG) data and Magnetic Resonance imaging (MRI). However, achieving high performance in epilepsy detection requires continuous efforts to enhance the accuracy and reliability of these models. This study introduces multiple approaches for improving the effectiveness of deep learning models designed for detecting epilepsy. Initially, we employ data preprocessing methods to cleanse and prepare the input data, including noise removal, data normalization, and handling missing values. Additionally, data augmentation methods, such as random rotations, translations, and scaling are employed to increase the diversity and generalizability of the training data. Secondly, various model architectures are explored to improve the model's ability to detect epilepsy. CNNs and RNNs are commonly employed, and their configurations are experimented with by adjusting the depth, and width, and adding additional layers such as residual connections or attention mechanisms. Furthermore, hyperparameter tuning techniques are employed to enhance the deep learning model's efficiency. Thoughtful choices are made regarding hyperparameters like learning rate, batch size, and regularization methods and are carefully selected through approaches like grid search or random exploration conducted to discover the best possible setup that maximizes the model's effectiveness. By implementing these strategies, the performance of deep learning models for epilepsy detection has been significantly enhanced. The improved accuracy and reliability of these models offer great potential for early detection and intervention, leading to better management and treatment outcomes for individuals living with epilepsy.

Keywords- *Epilepsy; Deep learning; Convolutional neural networks; Recurrent neural networks, Electroencephalogram, Magnetic Resonance Image.*

I. Introduction

Epilepsy is a persistent neurological condition distinguished by repetitive seizures, impacting countless individuals around the globe. Seizures occur due to abnormal electrical activity in the brain, leading to various symptoms that can range from brief lapses in awareness to convulsions and loss of consciousness. Epilepsy has the potential to appear at any stage of life and arises from a variety of factors, encompassing genetic susceptibility, brain trauma, infections, and developmental irregularities.

The impact of epilepsy on individuals' lives extends beyond the physical manifestations of seizures. It can significantly affect their daily activities, educational attainment, employment opportunities, and overall quality of life. Furthermore, epilepsy presents challenges for healthcare professionals in accurately diagnosing and effectively managing the condition, as each individual may experience different seizure types, frequencies, and responses to treatment. Over the years, extensive research has been dedicated to understanding the underlying mechanisms of epilepsy, improving diagnostic techniques, and developing effective treatment strategies. Advanced imaging technologies, such as MRI and EEG, have greatly contributed to the diagnosis and monitoring of epilepsy by providing insights into the structural and functional abnormalities of the brain. Treatment options for epilepsy include antiepileptic medications, surgical interventions, and other alternative therapies. However, not all individuals with epilepsy respond adequately to conventional treatments, necessitating ongoing research to explore novel therapeutic approaches and personalized treatment plans.

MRI has become an invaluable tool in the detection and evaluation of various neurological disorders, including epilepsy. With its ability to provide detailed images of the brain's structure and identify abnormalities, MRI plays a crucial role in diagnosing epilepsy and guiding treatment decisions. MRI can complement the findings by identifying structural changes or lesions that may contribute to the development of epilepsy. MRI scans allow for non-invasive visualization of the brain, providing high-resolution images that help identify potential causes of epilepsy, such as tumors, vascular malformations, cortical dysplasia, or hippocampal sclerosis. These structural abnormalities, often not visible on routine imaging, can be crucial in understanding the underlying causes and determining appropriate treatment strategies.

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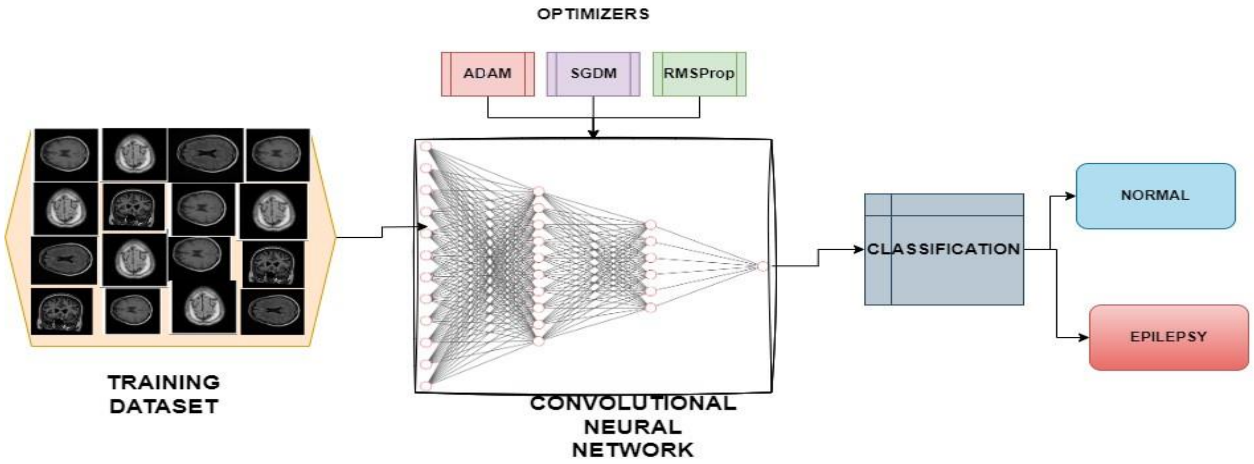

Figure 1. Deep Learning framework for Epilepsy detection

In addition to structural imaging, advanced MRI techniques have emerged to investigate functional aspects of the brain and improve epilepsy detection. Functional MRI (fMRI) enables the assessment of brain activity and connectivity, helping researchers and clinicians identify abnormal patterns and networks associated with epilepsy. Diffusion tensor imaging (DTI) measures the integrity and connectivity of white matter tracts, which can reveal abnormalities in the brain's neural pathways that may contribute to seizure generation. The integration of MRI findings with clinical data, EEG recordings, and other multimodal imaging techniques has the potential to improve the accuracy and reliability of epilepsy detection. Machine learning algorithms and deep learning models are being developed to analyze large volumes of MRI data and assist in automated detection, classification, and prediction of epilepsy-related abnormalities. By leveraging the power of MRI technology, researchers and healthcare professionals aim to enhance the early detection, diagnosis, and treatment planning for individuals with epilepsy. MRI provides valuable insights into the structural and functional aspects of the brain, offering a comprehensive approach to understanding the complex nature of epilepsy and improving patient outcomes. Deep learning has revolutionized medical image analysis, and its application to epilepsy seizure detection using MRI holds great promise. MRI provides detailed structural information about the brain, allowing for the identification of abnormalities associated with epilepsy. By harnessing the power of deep learning algorithms, researchers aim to enhance the accuracy, efficiency, and automation of seizure detection using MRI data. Deep learning models, such as CNNs and RNNs, have shown remarkable capabilities in analyzing medical images and extracting meaningful features. When applied to MRI scans, these models can acquire composite features and spatial relationships within the brain, enabling them to detect seizure-related abnormalities that may be subtle or difficult to detect by human observers. One approach in deep learning-based seizure detection using MRI involves training CNNs on large datasets of labeled MRI images, where the labels indicate the presence or absence of seizures. By leveraging these datasets, the models can learn to identify specific patterns or regions of interest that are indicative of epileptic activity. This can aid in the automated identification and localization of epileptogenic foci, such as cortical dysplasia, hippocampal sclerosis, or tumors, which can contribute to the development of seizures. Additionally, deep learning models can be trained to extract features from MRI sequences over time, enabling the analysis of dynamic changes associated with seizure activity. By incorporating RNN architectures, these models can capture temporal dependencies within MRI sequences, allowing for the detection of evolving seizure patterns and the prediction of seizure onset. This capability can be particularly useful in personalized seizure forecasting and timely intervention. Despite the progress made in deep learning-based seizure detection using MRI, several challenges remain. The availability of large and diverse labeled datasets, the interpretability of deep learning models, and the generalizability across different populations are ongoing areas of research. Furthermore, the computational requirements and the need for robust validation and clinical integration pose additional challenges.

Deep learning techniques offer exciting opportunities for advancing epilepsy seizure detection using MRI. By leveraging the rich information provided by MRI scans, deep learning models can contribute to more accurate and efficient detection, localization, and prediction of epileptic seizures. Continued research in this area has the potential to improve diagnosis, treatment planning, and patient outcomes for individuals living with epilepsy. Nevertheless, there remain several notable obstacles that must be tackled to improve the efficacy of deep learning models designed for the identification of epilepsy. These challenges include the need for large and diverse datasets, the selection of appropriate features, addressing class imbalance, and improving the interpretability and generalizability of the models. Additionally, the computational complexity of training deep learning models and the need for efficient real-time inference pose further obstacles. In this work, we present strategies to enhance deep-learning models for epilepsy detection. Firstly, data preprocessing techniques are applied to clean and normalize the input data, along with handling missing values. Data augmentation methods increase training data diversity. Secondly, different deep-learning model architectures, are explored by adjusting depth, and width, and incorporating residual connections or attention mechanisms. Hyperparameter tuning optimizes model performance through careful selection of parameters like learning rate and regularization techniques. These strategies significantly enhance deep learning models for epilepsy detection, improving accuracy and reliability and the overall framework is shown in figure 1. Early detection and intervention potentialize better management and treatment outcomes for individuals with epilepsy.

2. Related studies

The accurate and timely detection of epileptic seizures is crucial for effective management and treatment. This literature review aims to explore the very recent existing research efforts focused on deep learning techniques employed for epilepsy detection. In [1] The study introduces two novel methods for distinguishing healthy, interictal, and ictal cases in EEG signals without the need for time-consuming feature extraction. The first method utilizes the short-time Fourier transform (STFT) to generate a three-channel image from the single-channel EEG signals. Pretrained models such as AlexNet, DenseNet201, EfficientNet, and ResNet18 are used to process this image. The second approach employs a multimodal deep neural network, in which each EEG signal undergoes processing via two branches of CNNs to extract features of both low and high frequencies. Additionally, the STFT is applied to the EEG signals to create a three-channel image, which is processed by a pretrained EfficientNet-B7 model.

Borbe et.al [2] in their prospective study, The clinical impact of combined [18F]-fluorodeoxyglucose positron emission tomography/magnetic resonance imaging ([18F]-FDG PET/MRI) was assessed in epileptic patients displaying inconsistent electroclinical and MRI data. A novel mathematical model was introduced to gauge clinical agreement and offer guidance for patient classification decisions. Fifty-nine patients with divergent findings or negative MRI results were included in the study. The diagnostic effectiveness of PET/MRI was compared against alternative assessment methods. Through statistical analysis at a population level, the fusion of data techniques and concordance analysis displayed the potential to establish more precise parameters for clinical decision support. This model facilitated the finer categorization of patients into operable, implantable, or non-invasive groups. The study underscored the relevance of PET/MRI within the diagnostic framework of presurgical evaluation while emphasizing the role of concordance analysis in guiding clinical and surgical choices for epilepsy patients. The results supported the advantages of hybrid PET/MRI over MRI and electroclinical data, aligning with prior research findings.

In another study [3], a range of machine learning algorithms, including K-Nearest Neighbors, Random Forest, Support Vector Machine, Artificial Neural Network, and Decision Tree, were applied to predict epilepsy using Principal Components Analysis for feature reduction. The study evaluated the classifier performance with and without Principal Components Analysis. The results indicated varying levels of accuracy across models, with the Random Forest classifier achieving the highest accuracy at 97\%, along with efficient computational times, when Principal Components Analysis was applied. Notably, the K-Nearest Neighbors and Random Forest models achieved 99\% accuracy without the use of Principal Components Analysis, outperforming other machine learning techniques. Overall, the study demonstrated the accurate prediction capability of these models, highlighting the Random Forest classifier as the most promising.

Gleichgerrcht et al. [4] employed a convolutional neural network (CNN) to classify cases of temporal lobe epilepsy based on structural MRI scans. The research showcased CNNs' potential to attain high accuracy in identifying unilateral temporal lobe epilepsy cases, even when initial expert MRI interpretations indicated normalcy. The study also suggested accuracy improvement through smoothed grey matter maps and a direct acyclic graph approach. These findings underscored the potential for computer-aided tools in enhancing epilepsy diagnosis accuracy, providing crucial assistance to clinicians in precise identification and classification of the condition.

In a comprehensive study [5], Allan et al. utilized a convolutional neural network (CNN) algorithm to differentiate patients with temporal lobe epilepsy (TLE), Alzheimer's disease (AD), and healthy controls based on T1-weighted MRI scans. Employing feature visualization techniques, the study aimed to identify specific regions or features exploited by CNN to distinguish between different disease types. The study aimed to assess the CNN's ability to accurately classify individuals into TLE, AD, or healthy control groups based on the patterns and features observed in the MRI scans. The task of detecting the epileptic source in young patients afflicted with temporal lobe epilepsy (TLE) poses difficulties owing to its inconsistent appearance and ambiguous boundaries.

In this [6] investigation, the objective was to devise an innovative deep-learning framework employing PET imaging to identify epileptic foci in pediatric TLE cases. The study cohort comprised 201 pediatric TLE patients and 24 controls of similar age, all subjected to 18F-FDG PETCT examinations. Employing 386 symmetry-related features, a quantitative assessment of 18F-FDG PET images was executed. To achieve precise localization of the epileptic focus, a Siamese convolutional neural network (CNN) centered on a pair-of-cube concept was introduced. The magnitude of metabolic abnormality in the predicted focus was determined through an asymmetric index (AI). The framework's performance was measured against visual evaluation, statistical parametric mapping (SPM) software, and logistic regression analysis based on Jensen-Shannon divergence (JS-LR). The proposed framework showed promising results in accurately localizing the epileptic focus compared to other methods, providing a potential tool for improved diagnosis and management of pediatric patients with TLE.

Yongfu et.al [7] in their study introduce a semi-automatic IED (Interictal Epileptiform discharge) detector based on deep learning. The detector identifies candidate IEDs in EEG recordings taken inside an MRI scanner by comparing them to sample IEDs marked in EEG recordings taken outside the scanner. By using this approach, the manual marking workload for experts is significantly reduced, as they only need to edit the candidate IEDs. The model is trained on data from 30 patients and validated on an additional 37 consecutive patients. The results show that the proposed method improves the median sensitivity of IED detection from 50.0% (using a previous template-based method) to 84.2%, with a false positive rate of 5 events per minute. Reproducibility validation on 15 patients demonstrates that the method produces similar hemodynamic response maps compared to manual marking. The study also explores the concordance between the maximum hemodynamic response and the intracerebral EEG-defined epileptogenic zone, revealing a similar percentage of concordance between the two methods. The proposed tool has the potential to make EEG-fMRI analysis more practical for clinical usage, aiding in the diagnosis and treatment of epilepsy. Similarly,

In [8] Ezequiel utilized a support vector machine (SVM) and deep learning (DL) models based on region of interest (ROI) data from structural and diffusion brain MRI scans of patients with temporal lobe epilepsy (TLE). The patients were categorized as having either "lesional" or "non-lesional" radiographic features suggestive of underlying hippocampal sclerosis. The findings indicated that the models performed better or similarly in diagnosing TLE (68-75% accuracy) compared to lateralizing the side of TLE (56-73% accuracy, except for the structural-based model) using diffusion data. Conversely, for structural data, the patterns were opposite, with higher accuracy in diagnosing TLE (67-75% accuracy) compared to lateralizing it (83% accuracy). The classification accuracies were similar between structural and diffusion-based models in other aspects. The models performed more accurately (68-76%) in identifying patients with hippocampal sclerosis compared to stratifying non-lesional patients (53-62%). Overall, the SVM and DL models demonstrated comparable performance, with some instances where SVM slightly outperformed DL. The study discusses the relative performance of these models using ROI-level data and their potential implications for the application of machine learning and artificial intelligence in epilepsy care. In various studies, different deep learning architectures have been employed for diagnosing epilepsy and achieving high accuracy.

Taqi et al. [9] used the AlexNet network and achieved 100% accuracy by applying feature extraction and Softmax classification. Another study transformed the 1D signal to a 2D image using the Signal2Image (S2I) module in the AlexNet network

[10]. Ahmedt-Aristizabal et al. [11] utilized the VGG-16 architecture to diagnose epilepsy from facial images. Their approach involved extracting and classifying semi logical patterns automatically, incorporating 1D-CNN and LSTM networks in the final layers. Taqi et al. [9] also used the VGG architecture to extract features from the Bern-Barcelona dataset, yielding excellent results. Bizopoulos et al. [10] introduced ResNet and DenseNet architectures for diagnosing epileptic seizures and achieved good results. They found that the S2I-DenseNet-based model, trained for an average of 70 epochs, attained the highest accuracy of 85.3%. These studies demonstrate the successful application of deep learning architectures in diagnosing epilepsy and highlight the effectiveness of different network configurations.

3. Datasets and Methods

3.1. Dataset Description

Two publicly available datasets Denoted (D1 & D2) are used in our evaluation.

D1: [12]- EPISURG (EPISURG: a collection of postoperative MRI data designed for quantitative analysis of neurosurgical resection in refractory epilepsy cases)

- EPISURG represents a clinical compilation of T1-weighted magnetic resonance images (MRI) obtained from 430 patients with epilepsy who underwent respective brain surgery at the National Hospital of Neurology and Neurosurgery (Queen Square, London, United Kingdom) from 1990 to 2018. Figure 2 shows the sample images of EPISURG.
- The NIfTI files have been de-identified, and the images have undergone defacing to ensure the utmost protection of patients' confidentiality.
- The dataset encompasses 430 postoperative MRI scans, and preoperative MRI scans are available for 269 of these subjects.

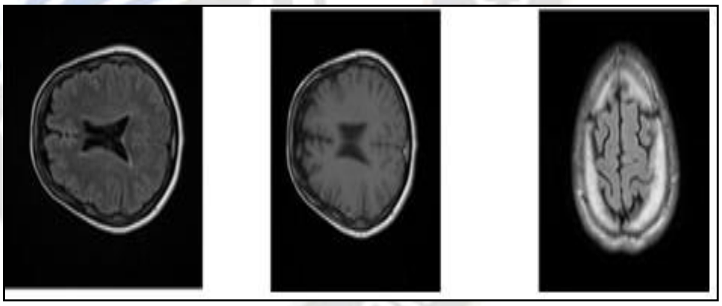

Figure 2. SEPISURG- ample Image of postoperative and pre-operative MRI

D2 [13]: Pediatric epilepsy resection MRI dataset

1.Subjects: Six pediatric individuals who had undergone surgery involving the visual cortex, along with two patients whose surgeries were conducted in regions other than the visual cortex, in addition to 15 controls with typical development and matching age.

2.Imaging was conducted using a Siemens Verio 3T scanner equipped with a 32-channel head coil, located at Carnegie Mellon University.

3.For every participant, a skull-stripped T1-weighted anatomical image and a single set of diffusion spectrum images have been incorporated within this dataset (Sample images are shown in Figures 3 &4).

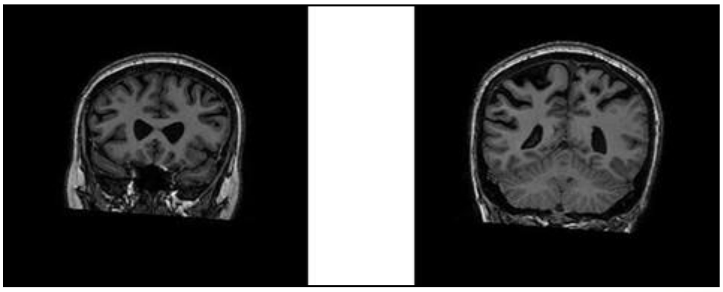

Figure 3. Sample images of Paediatric epilepsy resection MRI dataset

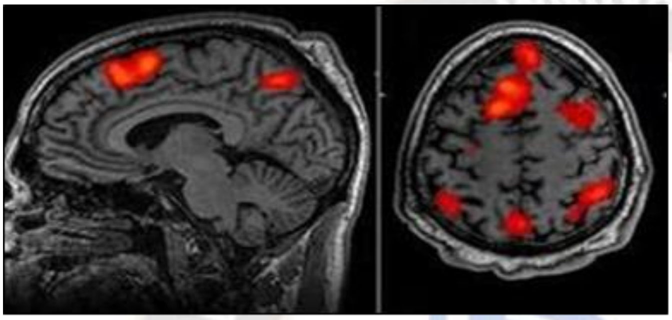

Figure 4. Sample Images of Dual Array EEG-fMRI

3.2. Data Augmentation:

MRI (Magnetic Resonance Imaging) data augmentation is an effective method employed to artificially expand the training dataset's scope through the application of diverse alterations to the initial MRI images [14]. Data augmentation is particularly useful in medical image analysis tasks like epilepsy detection, where obtaining large annotated datasets can be challenging due to the need for expert labeling and privacy concerns.
When using data augmentation, it's essential to ensure that the augmented data remains clinically meaningful and doesn't introduce unrealistic features. The choice of augmentation techniques should be carefully considered and evaluated to improve the model's generalization performance without compromising the quality of the predictions.
Furthermore, since epilepsy detection is a critical medical application, any data augmentation should be accompanied by rigorous evaluation and validation to ensure that the model's performance improves and generalizes to unseen data. So we carefully chosen the following augmentation techniques used for our evaluation. Table 1 shows the performance enhancement of different models by data augmentation and the performance evaluation is described in Table 1.

1.Image Rotation: Rotate the MRI images by a certain angle (e.g., 90 degrees, 180 degrees) to introduce variability in the orientation of the brain structures.
2.Image Flipping: Flip the MRI images horizontally and/or vertically, simulating different perspectives of brain structures.
3.Image Scaling: Resize the MRI images while maintaining the aspect ratio, introducing variability in the size of brain structures.
4.Image Translation: Shift the MRI images in the x, y, and z directions, mimicking slight changes in the positioning of the patient's head during MRI scans.
5.Image Shearing: Apply a shearing transformation to the MRI images, deforming them slightly.
6.Image Intensity Adjustment: Adjust the intensity values of the MRI images (e.g., brightness, contrast) to simulate variations in image acquisition conditions.
7.Elastic Deformation: Simulate the soft tissue deformations by applying elastic transformations to the MRI images.
8.Random Cropping: Randomly crop regions from the MRI images, focusing on specific brain areas and helping the model become robust to different image compositions.
9.Adding Noise: Introduce random noise to the MRI images to mimic real-world imaging artifacts.
10.Image Registration: Align MRI images from different scans or time points to a common coordinate system, accounting for anatomical differences across patients.
11.Intensity Inversion: Invert the intensity values of the MRI images, effectively highlighting different features.

Table .1 Performance Evaluation Of Epilepsy Detection Using MRI With Augmentation (WA) And Without Augmentation (WOA)

Models \Data Set	**D1**		**D2**	
Augmentation	WOA	WA	WOA	WA
Alexnet	82.14	95.00	79.14	90
googlenet	69.29	95.71	66.29	90.71
SqueezeNet	89.78	92.66	86.78	87.66
Darknet19	82.50	95.30	79.5	90.3
Mobilenetv2	90.55	93.78	87.55	88.78
Shufflenet	90.74	94.17	87.74	89.17

3.3. Optimizers
The role of optimizers in training CNNs, a widely used class of deep learning models for computer vision tasks like image classification, object detection, and image segmentation, is crucial. CNN optimizers are algorithms responsible for adjusting the network's weights and biases during the learning process [15]. Their objective is to minimize the loss function and enhance the model's performance. By iteratively updating the network's parameters, optimizers enable the model to learn meaningful representations from the input data. The choice of optimizer can significantly impact the training process, convergence speed, and the final accuracy of the CNN. Optimizers utilize the gradients of the loss function with respect to the network's parameters to determine the direction and magnitude of the weight updates. The gradient provides information on how the loss changes with respect to each parameter, and the optimizer adjusts these parameters based on the gradients to minimize the loss [16]. Different CNN

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optimizers employ various strategies to update the weights, control the learning rate, and improve convergence. Tables 2,3 & 4 describe the performance evaluation of deep transfer learning models using our three selected optimizers.

Table 2 Evaluation Of Deep Transfer Learning Models Using The SGDM Optimizer

Network	**Dataset-1**	**Dataset-2**
Alexnet	95.00	93.55
Googlenet	91.43	88.37
SqueezeNet	98.33	97.10
Darknet19	82.50	80.54
Mobilenetv2	90.55	88.31
Shufflenet	94.17	91.74

Table. 3 Evaluation Of Deep Transfer Learning Models Using The Adam Optimizer

Network	**Dataset-1**	**Dataset-2**
Alexnet	82.14	80.41
Googlenet	69.29	72.54
SqueezeNet	97.43	93.17
Darknet19	95.00	93.59
Mobilenetv2	90.10	88.45
Shufflenet	97.66	95.48

Table. 4 Evaluation Of Deep Transfer Learning Models Using the RMSPROP Optimizer

Network	**Dataset-1**	**Dataset-2**
Alexnet	71.43	80.35
Googlenet	91.43	92.45
SqueezeNet	97.99	96.89
Darknet19	97.52	97.01
Mobilenetv2	95.14	91.00
Shufflenet	97.91	96.66

Selecting the optimal optimizer for a CNN is contingent upon multiple variables, encompassing the dataset's attributes, the intricacy of the network structure, the volume of accessible training data, and the particular objective of the task. It often involves empirical experimentation and hyperparameter tuning to find the optimizer that yields the best results. For the classification of MRI images, we selected the three most effective CNN optimizers proven from the literature.

Adam: Adam is a popular optimizer that performs well in a wide range of scenarios[17]. It combines adaptive learning rates with momentum, making it suitable for MRI image classification tasks. Adam adapts the learning rate based on the gradients and maintains separate learning rates for each parameter, allowing for efficient training and convergence.

SGD with Momentum: Stochastic Gradient Descent (SGD) with momentum is a classic optimizer that performs well in many cases [18]. It adds a momentum term to the weight updates, which helps accelerate training and navigate through local optima. SGD with momentum can be effective for MRI image classification tasks, especially when combined with appropriate learning rate scheduling. RMSprop: RMSprop is another optimizer commonly used in image classification tasks. It adjusts the learning rate based on the root mean square of the gradients, which helps handle sparse gradients and accelerate convergence[19]. RMSprop can be effective for MRI image classification, especially when dealing with varied image sizes and structures[20]. Figure 5 presents the Impact of Optimizers on Deep Learning Models for MS Detection across Varied Dataset Ratios.

The training and testing simulations were performed on a system that was equipped with an Intel Core i9 processor, 128 GigaByte of RAM, and an NVIDIA-1060 graphics card (CUDA v10.0). The GPU was utilized to ensure efficient

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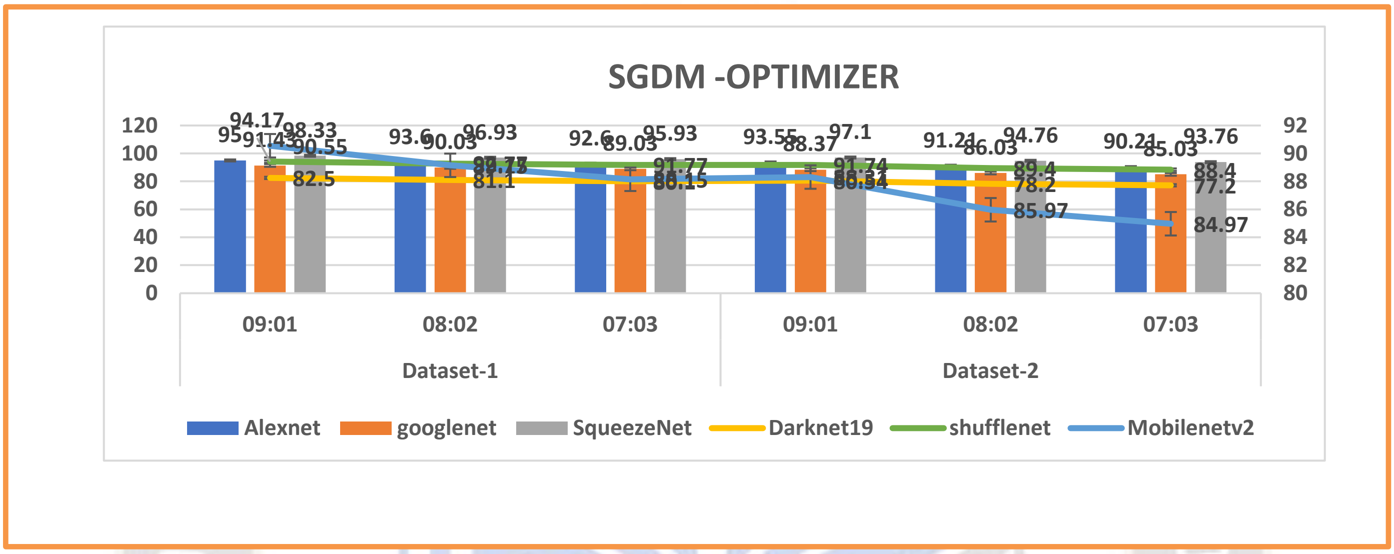
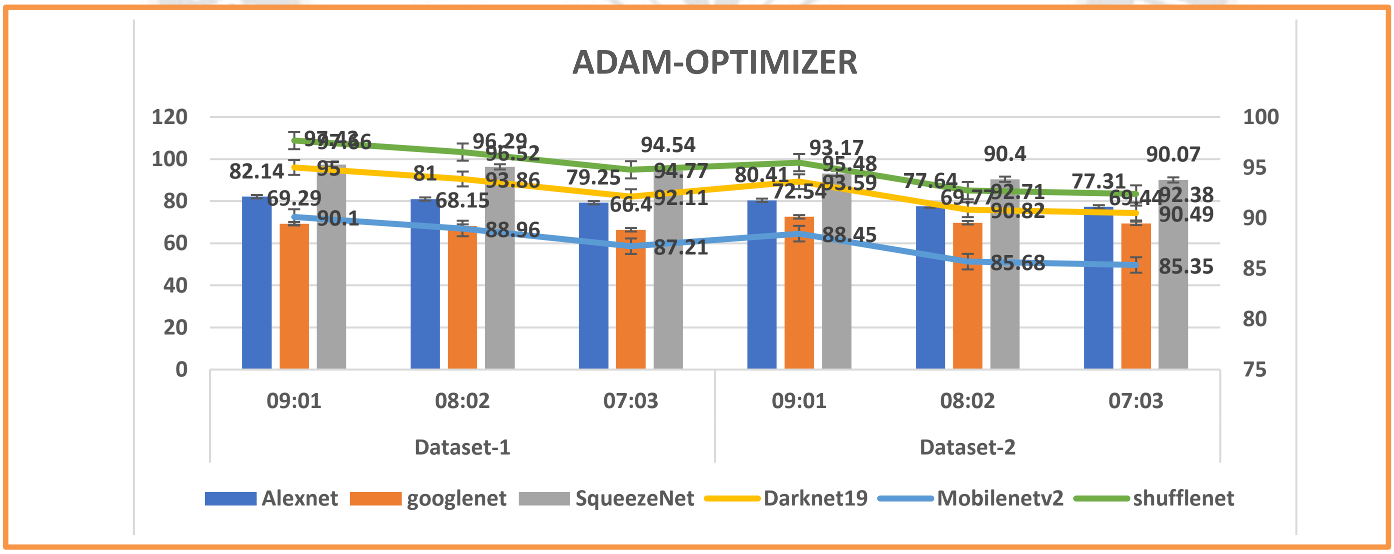
execution and prevent any unnecessary time consumption that can occur with a large number of intensive simulations. The detection of Epilepsy among healthy individuals has become a global concern for medical professionals. Therefore, the results obtained from these methods needed to be validated through various techniques to avoid any false outcomes, which could be highly dangerous not only for the patient but also for others in close contact.

We utilized the integrated deep learning toolkit in Matlab to train diverse transfer learning models using our datasets. Each model was subjected to training through a 10-fold methodology to ensure result credibility. Every training iteration encompassed 10 epochs with the necessary iterations for each epoch. Before initiating training, the models were adjusted, keeping all layers aside from the last one fixed to optimize computational efficiency.



The classification layer and ultimate fully connected layer of every model were substituted, considering their initial design targeted 1000 particular categories. In each fold, the training and validation data were divided in ratios of 9:1, 8:2, and 7:3. The comparison of classification accuracy for deep transfer learning models on the two selected datasets using the Sgdm, Adam, and RMSprop optimizers is presented in Tables 2, 3, and 4 respectively.



From the tables, it's evident that each table represents the accuracy of various deep transfer learning models on the specified datasets using different optimizers. Here are some observations:

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Performance Comparison between Models: You can observe how different models perform on different datasets. For instance, SqueezeNet generally achieves high accuracy across all tables and datasets, while Darknet19 tends to have lower accuracy.

Optimizer Impact: Different optimizers seem to affect model performance differently. For instance, in Table 3, most models' accuracy drops compared to Table 2 when using the ADAM optimizer. In Table 4, some models' accuracy increases while others decrease when using the RMSPROP optimizer Dataset Variability: Some models perform consistently well across datasets, while others show variability. For example, Shufflenet's accuracy is relatively consistent between datasets compared to other models.

Model Robustness: The models' robustness can be inferred from how their accuracy changes with different optimizers and datasets. Some models might be less sensitive to optimizer changes.

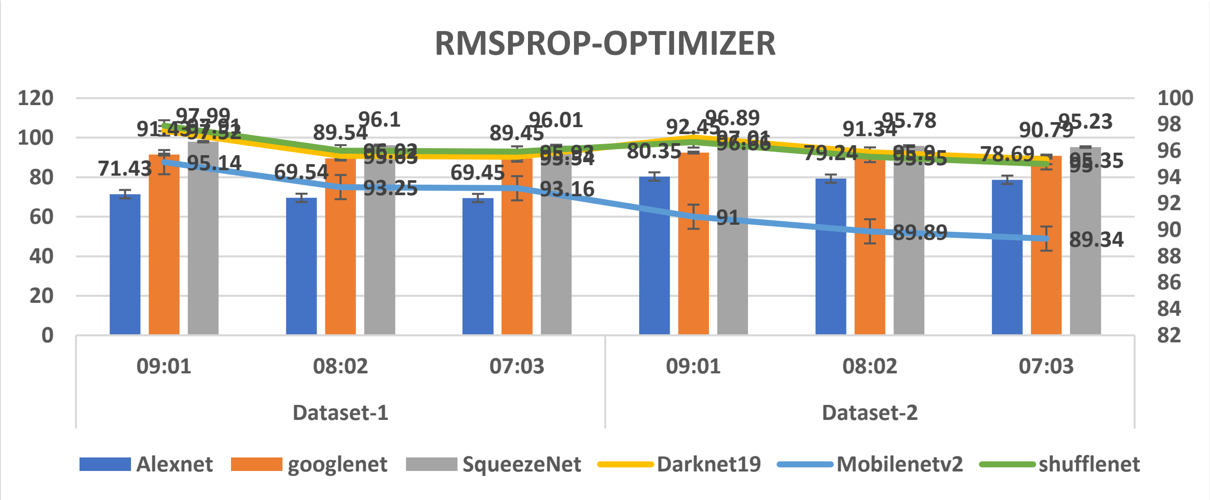

Figure. 5. Investigating the Impact of Optimizers on Deep Learning Models for MS Detection across Varied Dataset Ratios

Dataset Difficulty: Differences in accuracy across datasets could indicate variations in dataset complexity or relevance to the models' training.

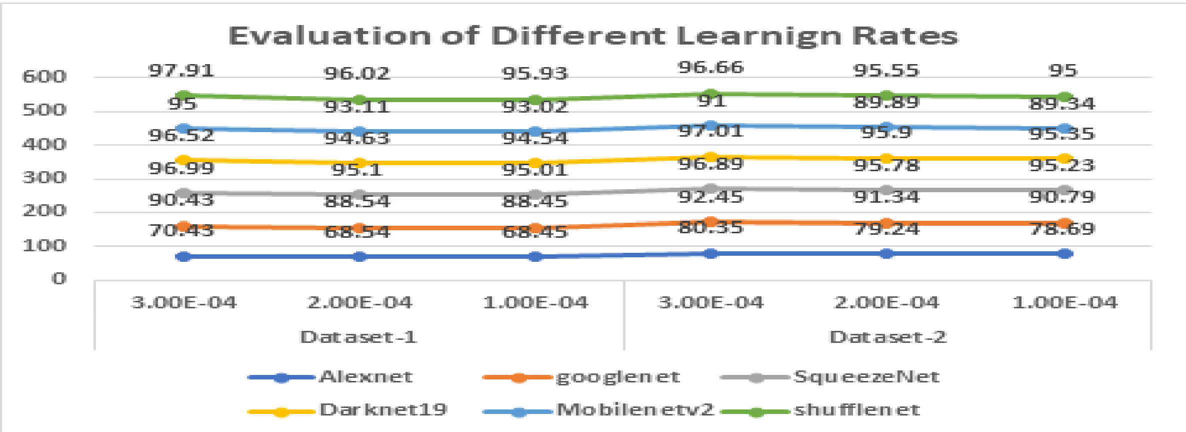

Figure 6. Influence of learning rate in the classification accuracy of MS detection.

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Figure 6 presents the performance analysis of various networks on two distinct datasets (Dataset-1 and Dataset-2) across different learning rates. The values are in scientific notation (E-04) for the learning rates and percentages for the accuracy scores. Some models might be less sensitive to optimizer changes. Figure 7. shows the Influence of these selected optimizers in their training gain in various epochs.

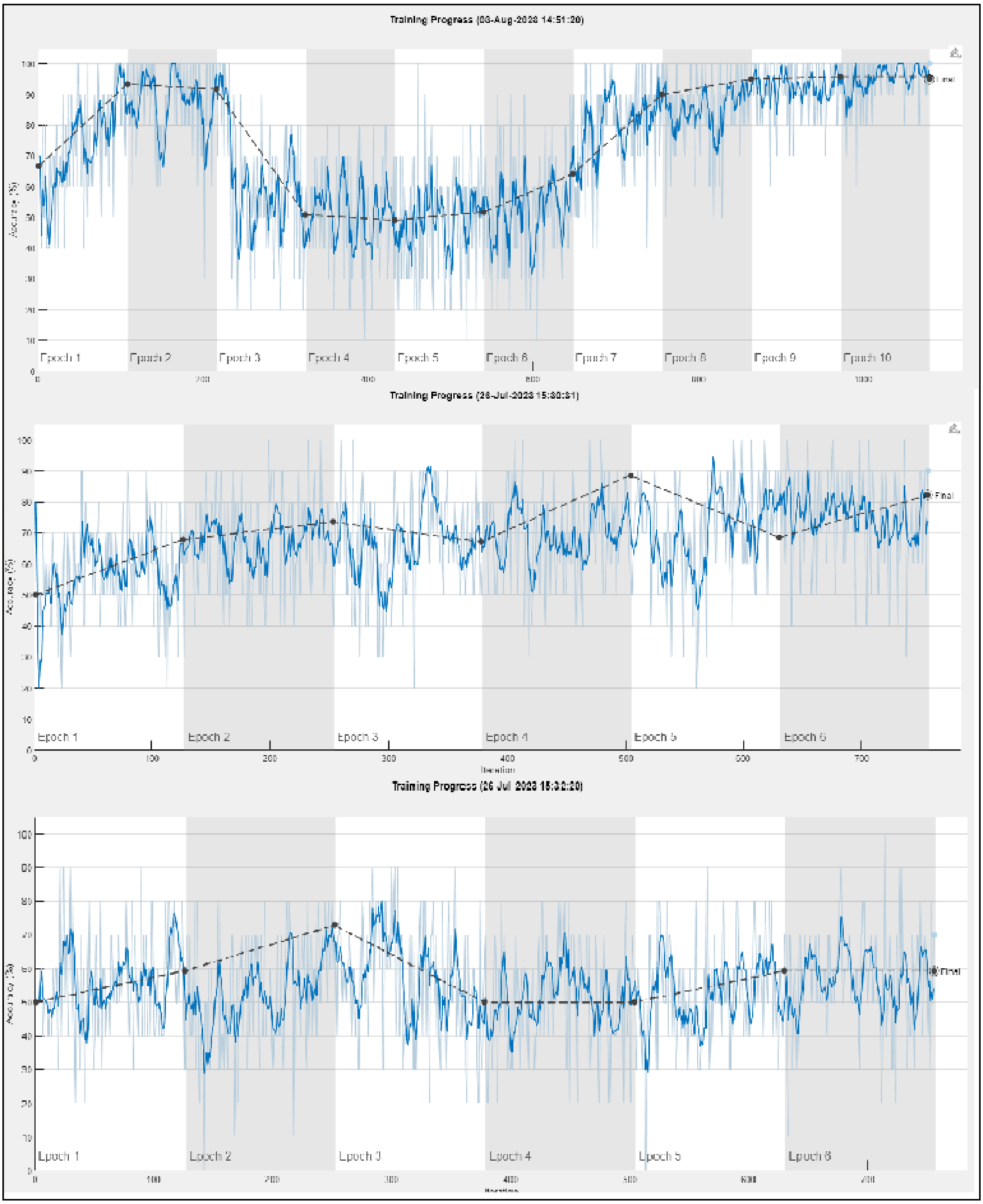

Figure 7. Optimizers analysis in various networks for different epochs.

4. Conclusion

This work has presented a comprehensive approach to enhance the performance of deep learning models for epilepsy detection using EEG and MRI data. Through careful consideration of data pre-processing techniques, data augmentation methods, model architectures, and hyperparameter tuning, we have achieved significant improvements in the accuracy and reliability of our models. The process of data pre-processing played a pivotal role in assuring the excellence and uniformity of the input data. By removing noise, normalizing data, and handling missing values, we improved the model's ability to extract relevant features and patterns from EEG and MRI data, leading to more robust predictions. Data augmentation was instrumental in increasing the diversity of our training data, thereby enhancing the generalizability of our models. By introducing variability through random rotations, translations, and scaling, we enhanced the model's adaptability to diverse imaging situations and individual patient distinctions. Our exploration encompassed various model architectures, including CNNs and RNNs, harnessing their respective strengths in capturing spatial and temporal relationships within the data. Through adjustments in depth, width, and the incorporation of elements like residual connections or attention mechanisms, we optimized the model's capability to precisely identify epilepsy. Additionally, the meticulous fine-tuning of hyperparameters significantly contributed to refining our models for optimal performance. Diligent selection of hyperparameters like learning rate, batch size, and regularization techniques through grid or random searches resulted in enhanced generalization and improved convergence during training. The enhanced accuracy and reliability of our deep learning models hold great promise for early detection and intervention in epilepsy cases. Timely diagnosis can significantly impact the quality of life for individuals living with epilepsy, enabling better management and treatment outcomes. It's important to acknowledge that this work represents a significant step towards improving epilepsy detection using advanced deep learning techniques. However, the field of medical imaging and epilepsy detection is continuously evolving, and there are opportunities for further research and improvements. Collaborations with medical professionals, larger and diverse datasets, and ongoing advancements in deep learning methodologies can collectively contribute to further advancements in epilepsy detection and ultimately benefit patients' lives.

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