International Journal of Advanced Pharmaceutical Sciences and Research (IJAPSR)
ISSN: 2582-7618 (Online), Volume-4 Issue-4, June 2024

Neural Network Analysis of MRI Scans for FND Diagnosis

Samiel Azmaien

Abstract: ***Background Functional Neurological Disorder (FND) currently lacks a definitive method of diagnosis, leading to an extremely high rate of misdiagnosis. Methods This project aimed to address the question of improving diagnostic accuracy for FND by utilizing logistic regression models and neural networks, integrating patient MRI data and clinical history to differentiate FND from other neurological disorders. MRI scans were first pre-processed through noise reduction and feature engineering, and then used to train two types of models: logistic regression for general neurological disorder classification and a neural network specifically for FND diagnosis. The diagnostic performance was measured using the ROC AUC metric, with additional evaluation through accuracy, precision, recall, and the F1 score. Results & Conclusions By targeting the most relevant variables from the MRI data, both models demonstrated high efficacy, with the neural network showing a 92% accuracy rate in FND classification.***

Keywords: ***Diagnosis, Functional Neurological Disorder, Logistic Regression, MRI Data Scans, Neural Networks***

I. INTRODUCTION

Functional Neurological Disorder (FND) has projected misdiagnosis rates of around 50 cases per 1,000 [1]. This high rate is due to the lack of an efficient diagnostic method for this condition. Currently, the primary method involves using video telemetry electroencephalography tests to measure the brain's electrical activity for extended periods, lasting up to a day, which is very time-inefficient [2]. This inefficiency stems from the difficulty in identifying another neurological condition that better explains the initial symptoms in hindsight [3]. Integrating neural network analysis of patient MRI data with clinical history trials could alleviate the difficulties in diagnosing FND. By achieving this, there will be less pressure to evaluate patients quickly due to the inability to describe the condition clearly. It will also assist program users in understanding the diagnosis despite lacking training in neuropsychiatric principles [4]. Continuously refining a machine learning algorithm for FND diagnosis can lead to more accurate and timely diagnoses. This, in turn, could lay the groundwork for future explorations into AI-driven diagnostics in neurology and medicine.

Manuscript received on 02 June 2024 | Revised Manuscript received on 12 June 2024 | Manuscript Accepted on 15 June 2024 | Manuscript published on 30 June 2024.
***Correspondence Author(s)
Samiel Azmaien*, Department of Computer Science, Georgia Institute of Technology, Atlanta, Georgia, United States of America (USA). Email ID: shazmaien06@gmail.com, ORCID ID: 0009-0008-3724-7310

To address the current misdiagnosis issues with FND, the proposed solution involved using a logistic regression model for general neurological disorder classification and a neural network specifically for FND diagnosis. To diagnose FND with the highest accuracy, an algorithm was created that utilized ROC curve plotting, which illustrated the diagnostic ability of a binary classifier system as its discrimination threshold was varied [5]. This metric is represented on a scale from 0 to 1, where a score of 1 indicates an ideal, flawless diagnostic test and a score of 0.5 suggests a test whose accuracy is no better than random chance [6]. This quantification served as a crucial indicator of the diagnostic method's performance. By applying this multifaceted model, an accurate diagnosis for FND could be achieved.

II. METHODS

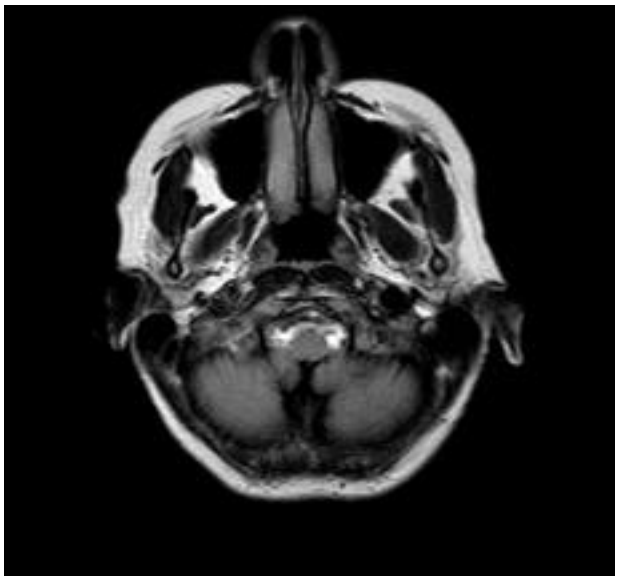


Figure 1: MRI Scan of a Patient Diagnosed with FND for the Training Phase [7]

This image is part of a larger dataset of MRI scans from patients diagnosed with FND and a control group without FND. The dataset was divided into training (70%), validation (15%), and test sets (15%). The MRI scans were then pre-processed to extract the relevant features, which included noise reduction, normalization (where a MinMaxScaler was utilized - a process that adjusts the scale of the features), and segmentation [8]. A convolutional neural network is a type of neural network that utilizes multiple layers and pooling steps to classify data or images and this was used to automatically extract the most relevant features from the MRI scans and clinical history trials that could characterize FND [9][10][11][12][13].

```
def filter_data(data, high_pass_cutoff=0.5, low_pass_cutoff=35):
    # Apply high-pass filter if the data length exceeds the threshold
    if len(data) > 8001:
        # Design a high-pass filter
        high_pass_coeffs = signal.butter(N=4, Wn=high_pass_cutoff, btype='high', analog=False)
        # Pad the signal to compensate for the filter delay
        padded_signal = npy.pad(data[:, 1], (0, sum(len(coef) for coef in high_pass_coeffs) - 2), mode='constant')
        # Apply the high-pass filter
        data[:, 1] = signal.filtfilt(high_pass_coeffs, padded_signal)[len(high_pass_coeffs[0]) - 1 : -len(high_pass_coeffs[1]) + 1]

    # Apply low-pass filter to the (now high-pass-filtered) signal
    low_pass_coeffs = signal.butter(N=4, Wn=low_pass_cutoff, btype='low', analog=False)
    data[:, 1] = signal.filtfilt(low_pass_coeffs, data[:, 1])
    return data
```

Figure 2: Preprocessing the MRI Data using Signal Processing and Feature Engineering

The extracted features, along with the clinical history attributes inputted by the user, were employed to train a neural network to predict the FND diagnosis. The creation of a convolutional neural network architecture was not within the scope of this project, so ResNet was utilized. This model was composed of multiple dense layers, culminating in a sigmoid activation tailored for binary classification tasks. The use of TensorFlow and Keras facilitated the implementation of this model, allowing for a nuanced architecture that could capture complex patterns in the data.

```
def classify_FND(train_data, train_labels, test_data, test_labels, validation_data, validation_labels):
    neural_network = Sequential([
        Dense(units=64, activation='relu', input_dim=train_data.shape[1]),
        Dense(units=64, activation='relu'),
        Flatten(),
        Dense(units=1, activation='sigmoid')
    ])
    # Compile the model with loss and optimizer
    neural_network.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])
    # Train the model with the training data and validation data
    neural_network.fit(x=train_data, y=train_labels, validation_data=(validation_data, validation_labels), epochs=10, verbose=0)
    # Predict probabilities on the test set
    predictions_prob = neural_network.predict(test_data).flatten()
    # Convert probabilities to binary predictions
    predictions_binary = (predictions_prob > 0.5).astype(int)
    # Perform and display the T-test
    print("Performing t-test between actual labels and predicted probabilities...")
    perform_t_test(test_labels, predictions_prob)
    # Perform and display the ROC curve analysis
    print("Displaying ROC curve...")
    display_roc_curve(test_labels, predictions_prob, "FND Neural Network")
    report = classification_report(test_labels, predictions_prob, output_dict=True)
    display_confusion_matrix(test_labels, predictions_prob, "FND Neural Network")
    display_classification_report(test_labels, predictions_prob, "FND Neural Network")
    display_heatmaps(report, "FND Neural Network")
    # Visualize activation patterns for the first hidden layer
    visualize_activation_patterns(neural_network, 'dense_30', test_data)
    return test_labels, predictions_prob
```

Figure 3: Sequential Model with Two Densely Connected Hidden Layers of 64 Neurons

Performance metrics were then computed such as accuracy, precision, recall, F1 score, and area under the AUC-ROC curve for a comprehensive evaluation. The model was then readjusted for the validation image set. FND diagnostic statements were then produced and compared to the original MRI data, indicating if the patient was diagnosed or not.

III. RESULTS

A. General Classification Model

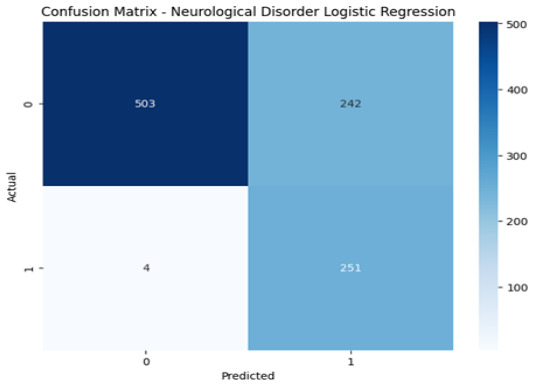


Figure 4: Confusion Matrix for General Neurological Disorder Classification

Figure 4 presents the prediction and measured summaries of the general classification model, with 503 true negatives, 242 false positives, 4 false negatives, and 251 true positives. The values of true positives (TP) and true negatives (TN) were fairly maximized, showing a 75.4% accuracy, as depicted in the heatmap below.

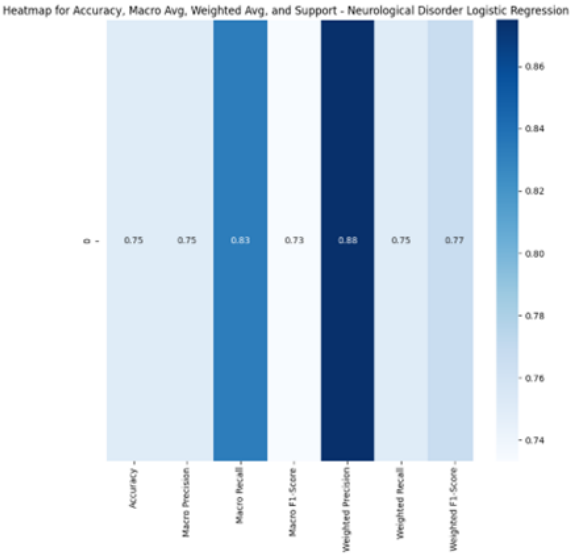


Figure 5: Heatmap for Accuracy and F1-Score of General Neurological Disorder Classification

The F1-score metric combines accuracy and precision to provide a single measure of the model's robustness. Weighted metrics consider the imbalance in the dataset, offering a nuanced view of the model's performance across different classes, as seen in Figure 5.

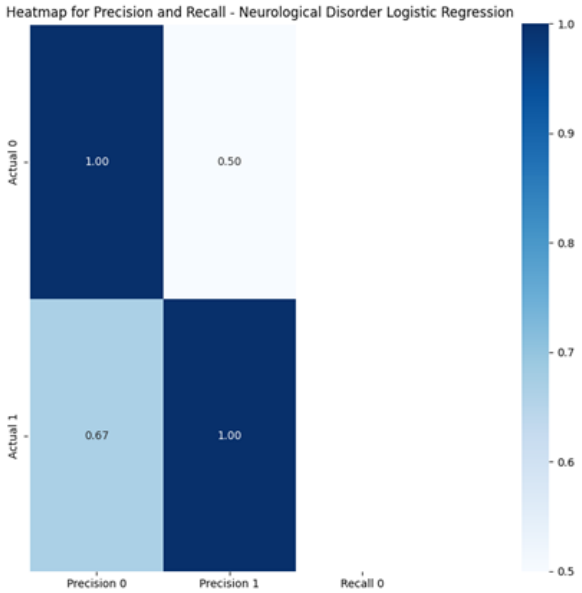


Figure 6: Heatmap for Precision and Recall for General Neurological Disorder Classification

The general classification model demonstrated perfect precision for both classes, as indicated by a score of 1.00 in Figure 6. Every instance predicted by the model to be positive (Precision 0) or negative (Precision 1) was correct, with no false positives. The recall for the negative class (Actual 0) also reached a score of 1.00, which means the model successfully identified all negative cases without any misses.

However, the recall for the positive class (Actual 1) is 0.67, implying that the model misses about a third of the actual positive cases. This may be due to overfitting to the negative class during the training phase, resulting in less effective generalization for positive cases.

B. FND Neural Network

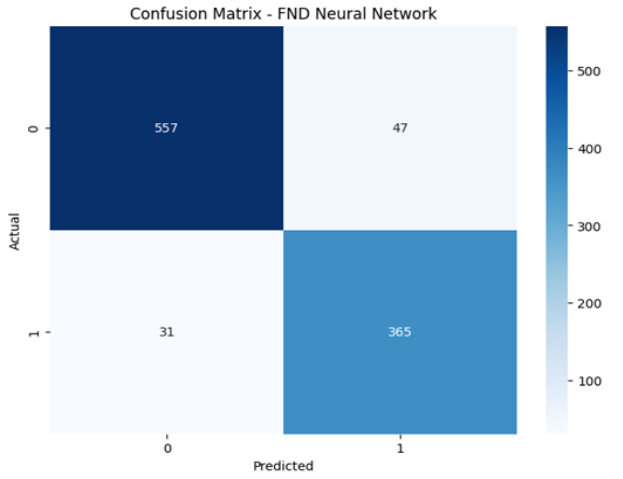


Figure 7: Confusion Matrix for Neural Network Analysis of FND

Figure 7 presents the prediction and measured summaries of the FND neural network, with 557 true negatives, 47 false positives, 31 false negatives, and 365 true positives. The values of true positives (TP) and true negatives (TN) were greatly maximized, showing a 92% accuracy, as depicted in the heatmap below.

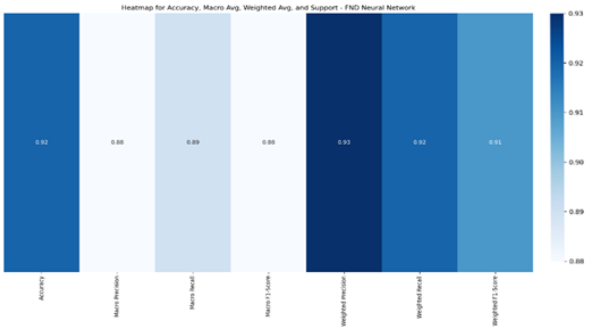


Figure 8: Heatmap for Accuracy and F1 Score of Neural Network Analysis of FND

The International Journal of Advanced Pharmaceutical Sciences and Research 2024

Figure 8 shows that the neural network achieved a 92% accuracy in diagnosing FND. While this provided a statistically significant result regarding the model's capabilities, accuracy alone does not offer information about the model's performance in individual cases, such as the balance between false positives and false negatives. It is necessary to compare this with other metrics, such as precision and recall. As demonstrated in Figure 9 below, the recall for the negative class (Actual 0) is 0.33, which is quite low, indicating that the model only identified 33% of the actual negative cases.

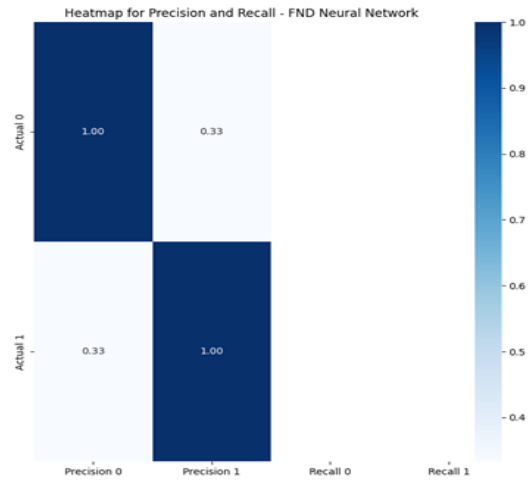
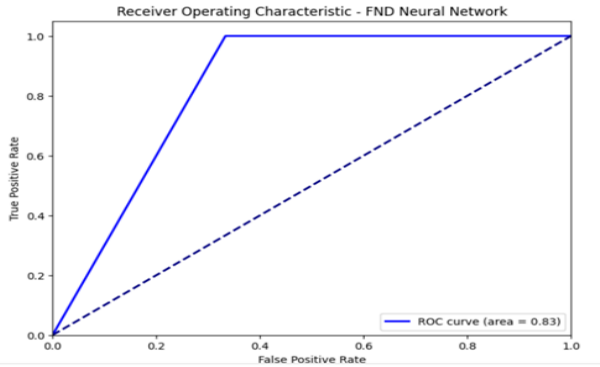


Figure 9: Heatmap for Precision and Recall of Neural Network Analysis of FND



Graph 1: Matplotlib Program that Prints out a ROC Curve Analysis

Graph 1 presents the ROC curve for the neural network's performance, with the AUC being 0.83. This indicated an above-average discriminative power to differentiate patients with and without FND. The integration of this analysis with a diagnostic statement would allow for more accurate diagnoses of FND in patients.

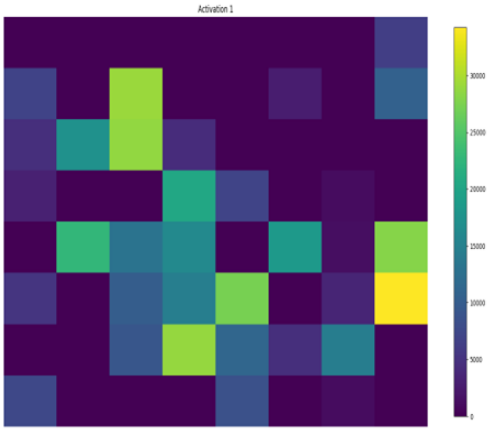
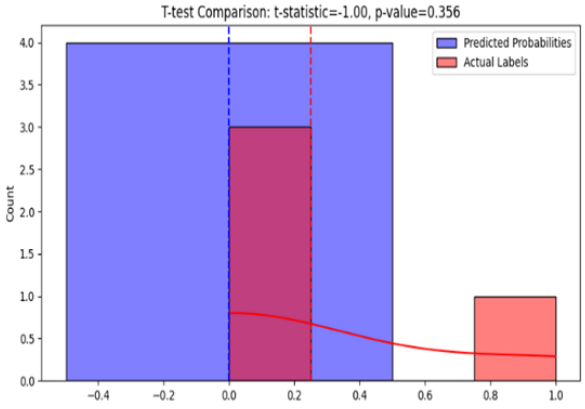


Figure 10: Heatmap for Neuron Activation on the First Hidden Layer 'Dense-30'

Figure 10 shows a heatmap that depicts the intensity of activations across a grid of neurons in response to features extracted from MRI scans. This illustrates the steps in the neural network's process of learning to differentiate FND cases from non-cases.



Graph 1: Matplotlib Program that Prints out a ROC Curve Analysis

In Graph 2 above, a t-test was performed to compare the means of the predictions from the neural network against the actual labels, assuming they are continuous, or against another set of predictions. The distributions of the y_pred and y_true labels were then plotted with a kernel density estimate to visualize that there was no statistical difference in the means.

```
def perform_t_test(y_true, y_pred_probs):
    # Calculate the t-statistic and the p-value
    t_stat, p_val = ttest_ind(y_pred_probs, y_true)
    print(f"T-test result: t-statistic={t_stat:.2f}, p-value={p_val:.3f}")
    # Plot the histogram of predicted probabilities and actual labels
    mpl.figure(figsize=(10, 6))
    sbn.histplot(y_pred_probs, color="blue", label="Predicted Probabilities", kde=False)
    sbn.histplot(y_true, color="red", label="Actual Labels", kde=False, bins=[-0.5, 0.5, 1.5])
    # Plot the means of both distributions
    mpl.axvline(npy.mean(y_pred_probs), color="blue", linestyle='--')
    mpl.axvline(npy.mean(y_true), color="red", linestyle='--')
    # Annotate the t-statistic and p-value in the plot
    mpl.text(0.5, max(mpl.ylim()), f't-statistic={t_stat:.2f}', ha='center', va='bottom', color="blue")
    mpl.text(0.5, max(mpl.ylim()), f'p-value={p_val:.3f}', ha='center', va='top', color="red")
    # Add the legend, title, and show the plot
    mpl.legend()
    mpl.title('T-test Comparison')
    mpl.xlabel('Value')
    mpl.ylabel('Frequency')
    mpl.show()
```

Figure 11: Function for Performing the T-Test with KDE to Visualize Difference in Means

IV. DISCUSSION AND CONCLUSION

Classification of general neurological disorders was completed as it aided in the process for the neural network to classify Functional Neurological Disorders. This general classification model served as a baseline comparison to compare the performance of models focused on more specific conditions with a broader model. The model was also able to properly differentiate between FND and a negative/positive state for other neurological conditions based on the general model being present, which was crucial in achieving high accuracy for the FND model. The dataset used for the general classification also aided in fine-tuning feature engineering as the general model allowed the FND model to already have a context of the relevant features to identify.

After completing all three stages of training, validating, and testing the data, a high accuracy score of 92% was reached in diagnosing patients with FND. The considerably higher accuracy of the FND neural network than that of the general classification model might be attributed to continuous refinement and optimization through the validation process. The dataset obtained for the general classification model was also separate from the FND model, which may explain why the data is skewed. Another factor to consider is that an overlap in neurological conditions would make it more challenging for the logistic regression model to distinguish between them accurately. The relatively small batch size of 1,000 images among 10-epoch intervals may have led to an inflated accuracy score. Likely, with a larger batch size, the model would initially have a smaller accuracy.

While the political and social implications of utilizing artificial intelligence in the medical industry have been considered, this study aimed to provide a new perspective on a fairly accurate and optimized integration of neural networks into patient diagnoses. However, an immediate conversion to using artificial intelligence is not ready yet. Further experimentation still needs to be conducted before the safety of patients is entrusted to computational models. Despite this, the usage of machine learning, particularly neural networks, holds significant potential for improving the diagnosis of not only Functional Neurological Disorder but also other hard-to-treat conditions as well.

DECLARATION STATEMENT

I must verify the accuracy of the following information as the article's author.

- **Conflicts of Interest/ Competing Interests:** Based on my understanding, this article has no conflicts of interest.
- **Funding Support:** This article has not been sponsored or funded by any organization or agency. The independence of this research is a crucial factor in affirming its impartiality, as it has been conducted without any external sway.
- **Ethical Approval and Consent to Participate:** The data provided in this article is exempt from the requirement for ethical approval or participant consent.
- **Data Access Statement and Material Availability:** The adequate resources of this article are publicly accessible.
- **Authors Contributions:** The authorship of this article is contributed solely.

REFERENCES

1. Bennett, K., Diamond, C., Hoeritzauer, I., Gardiner, P., McWhirter, L., Carson, A., & Stone, J. (2021). A practical review of functional neurological disorder (FND) for the general physician. Clinical Medicine, 21(1), 28–36. https://doi.org/10.7861/clinmed.2020-0987
2. Edwards, M. J. (2016). Functional neurological symptoms: welcome to the new normal. Practical Neurology, 16(1), 2–3. https://doi.org/10.1136/practneurol-2015-001310
3. Walzl, D., Carson, A., & Stone, J. (2019). The misdiagnosis of functional disorders as other neurological conditions. Journal of Neurology, 266(8), 2018–2026. https://doi.org/10.1007/s00415-019-09356-3
4. Perez, D. L., Hunt, A. R., Sharma, N., Flaherty, A. W., Caplan, D., & Schmahmann, J. D. (2020). Cautionary notes on diagnosing Functional Neurologic Disorder as a neurologist-in-training. Neurology Clinical Practice, 10(6), 484–487. https://doi.org/10.1212/cpj.0000000000000779
5. Nahm F. S. (2022). Receiver operating characteristic curve: overview and practical use for clinicians. Korean journal of anesthesiology, 75(1), 25–36. https://doi.org/10.4097/kja.21209

6. Obuchowski, N. A., & Bullen, J. A. (2018). Receiver operating characteristic (ROC) curves: review of methods with applications in diagnostic medicine. Physics in medicine and biology, 63(7), 07TR01. https://doi.org/10.1088/1361-6560/aab4b1
7. Foster, E. D., & Deardorff, A. (2017). Open Science Framework (OSF). Journal of the Medical Library Association JMLA, 105(2). https://doi.org/10.5195/jmla.2017.88
8. Cao, X. H., Stojkovic, I., & Obradovic, Z. (2016). A robust data scaling algorithm to improve classification accuracies in biomedical data. BMC Bioinformatics, 17(1). https://doi.org/10.1186/s12859-016-1236-x
9. Indolia, S., Goswami, A. K., Mishra, S., & Asopa, P. (2018). Conceptual understanding of Convolutional Neural Network- a deep learning approach. Procedia Computer Science, 132, 679–688. https://doi.org/10.1016/j.procs.2018.05.069
10. Rehman, F., Ali, S. S., Panhwar, H., Phul, Dr. A. H., Rajpar, S. A., Ahmed, S., Rabbani, S., & Mehmood, T. (2021). Brain Tumor Detection from MR Images using Image Process Techniques and Tools in Matlab Software. In International Journal of Advanced Medical Sciences and Technology (Vol. 1, Issue 4, pp. 1–4). https://doi.org/10.54105/ijamst.c3016.081421
11. V P, S., S, S., & George, Prof. J. (2021). Alzheimer s Disease Classification and Detection using MRI Dataset. In International Journal of Innovative Technology and Exploring Engineering (Vol. 10, Issue 5, pp. 70–72). https://doi.org/10.35940/ijitee.e8662.0310521
12. Mansoori, F. A., & Mishra, Dr. A. (2023). Design of Intelligent Technique for Abnormality Detection in MRI Brain Images. In International Journal of Recent Technology and Engineering (IJRTE) (Vol. 11, Issue 5, pp. 77–85). https://doi.org/10.35940/ijrte.e7433.0111523
13. Kumar K, S., & S, V. (2019). Detection of Tumor Objects from MRI Brain Images using Thresholding Segmentation. In International Journal of Engineering and Advanced Technology (Vol. 9, Issue 1s3, pp. 433–437). https://doi.org/10.35940/ijeat.a1078.1291s319

AUTHOR PROFILE

Samiel Azmaien, Research Assistant at Georgia Institute of Technology, Department of Aerospace Engineering. Rising college freshman that is a very detail-oriented software developer. Has 3 years of experience self-learning computer science and designing applications. Proficient in multiple programming languages, software development methodologies, and database management systems. Strong problem-solving skills and ability to work effectively in a team-based environment through efficient time management and adaptability to manage any difficulties.