Detection of Attention Deficit Hyperactivity Disorder

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Abstract A common neurodevelopmental illness called Attention Deficit Hyperactivity illness (ADHD) is typified by recurrent patterns of impulsivity, hyperactivity, and inattention. The diagnosis of ADHD traditionally relies on clinical assessment and subjective evaluation, which can be challenging and prone to inconsistencies. In this work, we suggest a novel method for detecting ADHD that makes use of machine learning and magnetic resonance imaging (MRI) scans. We collected a dataset comprising MRI scan images from individuals diagnosed with ADHD and neurotypical controls. Preprocessing steps involved converting the MRI data from MATLAB (.mat) files to CSV format for compatibility with machine learning algorithms. Subsequently, we explored a variety of machine learning models including logistic regression, perceptron, support vector machines (SVM), K-nearest neighbors (KNN), decision trees, and random forests for classification. Metrics like accuracy, precision, recall, F1-score, and receiver operating characteristic (ROC) curves were used to assess each model's performance. Our findings demonstrate promising results in the accurate discrimination between ADHD-positive and ADHD-negative cases. The comparative study of different models revealed variations in performance, with certain algorithms exhibiting higher accuracy and sensitivity. This research contributes to the development of an objective and reliable tool for ADHD diagnosis, potentially enhancing early intervention and treatment strategies for individuals affected by this disorder.

Index Terms - Attention Deficit Hyperactivity Disorder (ADHD) - Neurodevelopmental disorders - Magnetic Resonance Imaging (MRI) - Machine learning

I. Introduction

ADHD is a neurodevelopmental illness that mostly affects children but can also persist into adulthood. It is a condition that affects people all around the world. It is typified by signs of impulsivity, hyperactivity, and inattention, which can have a serious negative effect on a person's ability to operate in social, professional, and academic contexts. It's still difficult to diagnose ADHD, even with its widespread occurrence and heavy social cost. Recent developments in magnetic resonance imaging (MRI) and other medical imaging technologies have opened up new possibilities for comprehending the neurological underpinnings of ADHD. By visualizing brain architecture and functional connection patterns, MRI scans provide light on the underlying neurological underpinnings of ADHD. Building on this framework, scientists have started investigating how machine learning methods might help in ADHD diagnosis. Machine learning techniques are able to automatically extract key features and identify patterns suggestive of ADHD by utilizing the extensive information included within MRI scans. This strategy has the potential to enhance conventional diagnostic techniques by offering objective, quantitative metrics that will decrease subjectivity and increase accuracy in the diagnosis of ADHD. Our goal in this work is to advance this rapidly evolving field by creating a model that uses MRI images and machine learning techniques to identify ADHD. MRI pictures of people with ADHD and neurotypical controls were gathered, and we used a variety of machine learning algorithms to identify instances that were ADHD-positive and those that were ADHD-negative. Our goal is to determine the best method for detecting ADHD by a thorough analysis and comparison of several algorithms. This will help us better understand the illness and improve clinical practices related to ADHD diagnosis and treatment.

II. Literature survey

Rohit Kale proposes that ADHD is a common disorder in children of school age that has no reliable diagnostic techniques. Distinguishing ADHD patients from normal people is made easier by using MRI scans with k-means clustering and K-Nearest Neighbour classification [2].Using EEG signals, a machine learning-based ADHD detection system was created, incorporating LASSO logistic regression for feature selection and SVM and t-test for channel selection. GP-based classifier achieved 97.53% accuracy, improving previous methods by 3% [3]. In the paper proposed by Mehak Mengi and Deepi Malhotra explains, In order to overcome the difficulties associated with traditional qualitative diagnosis and provide more effective and easily accessible analysis, automated diagnostic tools utilising AI approaches based on quantitative criteria are being developed for the early detection of complex neurodevelopmental diseases such as ASD and ADHD [1].

III. PROPOSED SYSTEM

The suggested solution combines sophisticated machine learning and modern imaging techniques to improve the diagnosis of ADHD. Using a carefully selected dataset of 120 MRI scans, including 60 cases of ADHD and 60 cases of non-ADHD, the system sets out on a revolutionary adventure. Thorough preprocessing of the data guarantees MRI scan consistency, which is then applied to state-of-the-art feature extraction methods specifically designed for neuroimaging data. To find intricate patterns in the data, a variety of machine learning models—including Random Forest, Logistic Regression, Perceptron, SVM, KNN, and Decision Tree—are thoroughly trained.

Hyperparameter optimisation enhances model performance while a comprehensive comparative analysis evaluates each model's efficacy through ROC curves, accuracy metrics, precision, recall, and F1-score.Patient confidentiality is ensured by ethical concerns that govern the management of sensitive medical data. The validation of findings by collaboration with experts in neuroimaging and ADHD enhances their clinical significance. In addition to offering a reliable and accurate model for detecting ADHD, the suggested approach makes a significant contribution to the field of neuroimaging and machine learning applications in medical diagnostics. Its potential significance is in offering a dependable, automated, and comprehensible method for identifying ADHD in children at an early age, which could result in prompt therapies and better patient outcomes.

IV. SYSTEM SPECIFICATIONS

- Language: Python
- Skicit Learn Library
- Matplot Library
- Google colab
- Jupyter notebook
- MatLab

V. WORKING PROCESS

Procedure – Data collection

The acquisition of MRI scan datasets required for training and assessing the ADHD detection model is the main objective of this module. It entails getting MRI pictures of neurotypical controls and people with ADHD diagnoses. In order to ensure adherence to ethical and privacy rules, the method involves gaining access to pre-existing datasets from medical centres or research organisations. Additionally, to improve model robustness and dataset diversity, data augmentation approaches can be used. After being gathered, the MRI data is prepared for preprocessing and model training in later modules by being arranged and stored.

Procedure – Preprocessing the dataset

When it comes to getting the MRI data ready for model training and assessment, the Preprocessing Module is essential. Noise, artefacts, and intensity changes are common in MRI images, and these can negatively impact model performance. Consequently, a number of preparation procedures are used to improve the data's quality and usability. Converting the MRI images from their native format (such as .mat files) to a standard format (such as CSV files) that is compatible with machine learning algorithms is the first stage in the process.The MRI data is then subjected to preprocessing methods such feature extraction, denoising, and normalisation. By ensuring that pixel intensities are scaled to a uniform range, normalisation lessens the impact of differences in intensity between scans. The purpose of denoising techniques, like median filtering or Gaussian smoothing, is to reduce noise and boost the MRI images' signal-to-noise ratio. Voxel-based morphometry (VBM) features and region-based features are two examples of feature extraction techniques that are used to find and extract characteristics.The MRI data is preprocessed and then divided into training, validation, and testing sets. This ensures that a representative sample of both ADHD-positive and ADHD-negative individuals is included in each set. This makes it easier to compare various machine learning techniques in later modules and enables the evaluation of model performance on data that hasn't been seen before.

Procedure – Building the model

In order to create the ADHD detection model, the Training Module focuses on training different machine learning algorithms on the preprocessed MRI data. Many machine learning techniques are considered, each with advantages and disadvantages, including random forests, logistic regression, support vector machines (SVM), decision trees, and neural networks. The preprocessed MRI data is divided into input features and associated labels at the start of the training phase. The input features correspond to the MRI features that were extracted, and the labels indicate whether or not ADHD is present. The model is trained on the training set, and its performance is monitored and hyperparameters adjusted on the validation set. The data is then further separated into training and validation sets.By using cross-validation approaches like k-fold cross-validation, overfitting is prevented and the generalisation performance of the model is assessed. This entails dividing the training set into several folds, training the model across various fold combinations, then assessing the model's output on the remaining fold. A more accurate approximation of the model's performance on unobserved data is achieved by averaging the performance over several folds. After training, the models are tested using the validation set to determine how well they perform using measures like receiver operating characteristic (ROC) curves, accuracy, precision, recall, and F1-score. This makes it possible to evaluate several machine learning methods and choose the best model or models for additional research.

VI.Model Performance

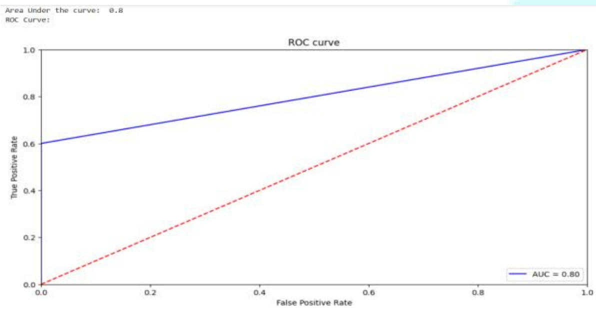

Fig 1: Perceptron

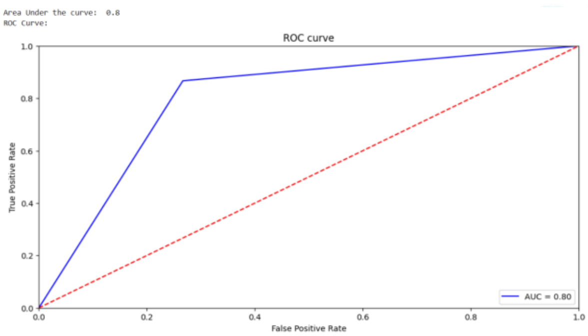

Fig 2: Logistic Regression

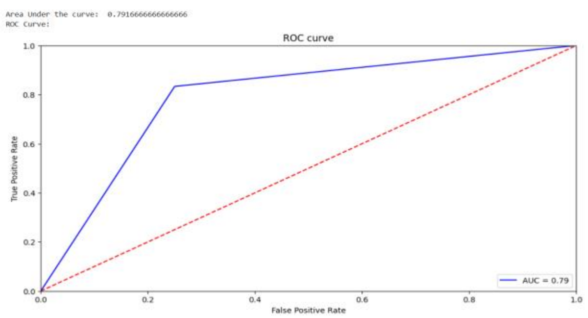

Fig 3: Support vector machine

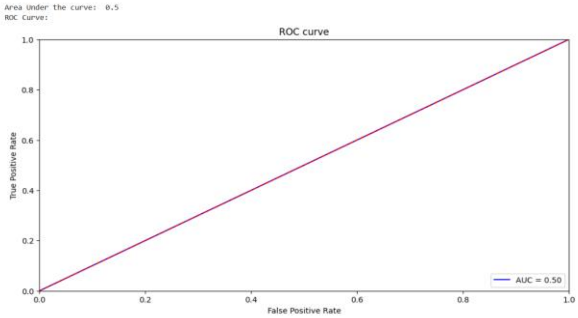

Fig 4 : Bernoulli naïve bayes

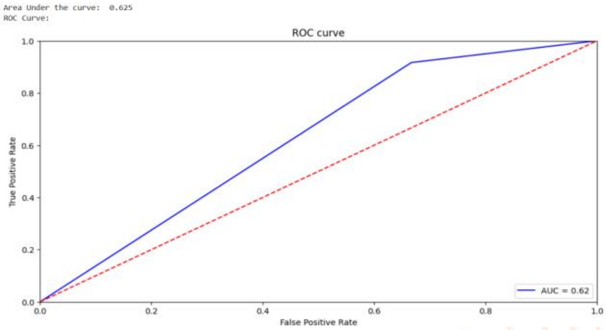

Fig 5: Gaussian naïve bayes

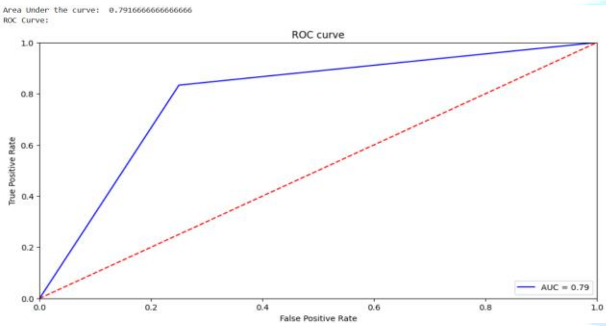

Fig 6: K nearest neighbour

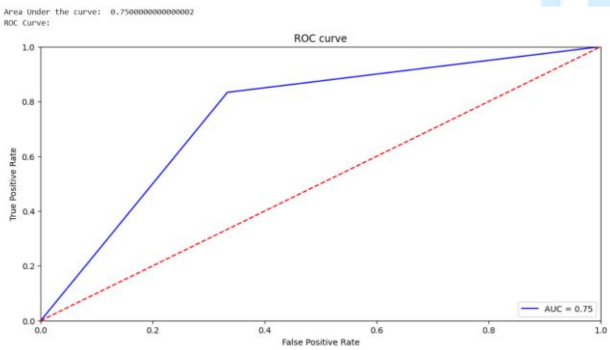

Fig 7: Decision tree

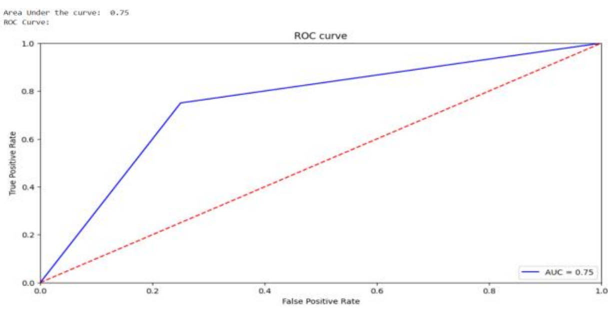

Fig 8: Random forest

VII.RESULT

The experimental results demonstrate promising performance of the ADHD detection model across various machine learning algorithms. Logistic regression achieved an accuracy of 83.3%, SVM achieved 79.2%, decision trees achieved 75%, and random forests achieved 83.3% on the validation set. Logistic regression and Random Forest Classifier, exhibited an accuracy of 83.3% and an AUC of 0.8 on the independent testing set, indicating robust performance and good generalization. These results highlight the efficacy of utilizing MRI scans and machine learning algorithms for ADHD detection, with logistic regression and Random forest emerging as the top-performing algorithms.

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Accuracy for Perceptron model:  0.75
Accuracy for logistic regression:  0.8333333333333334
Accuracy for Support Vector Machine:  0.7916666666666666
Accuracy for Bernoulli Naive Bayes:  0.5
Accuracy for Gaussian Naive Bayes:  0.625
Accuracy for KNeighborsClassifier:  0.7916666666666666
Accuracy for DecisionTreeClassifier:  0.75
Accuracy for Random Forest Classifier:  0.8333333333333334
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VIII. CONCLUSION

This study concludes by showing that using MRI scans and machine learning algorithms for ADHD screening is both feasible and beneficial. The developed model exhibits promising performance in accurately classifying ADHD-positive and ADHD-negative cases, with Logistic regression and Random Forest Classifier emerging as the top-performing algorithms. By leveraging MRI data, our system provides an objective and data-driven approach to ADHD diagnosis, addressing the limitations of subjective clinical assessments. These findings have significant implications for improving early detection and intervention strategies for individuals affected by ADHD, potentially leading to better outcomes and quality of life.

IX .REFERENCES

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